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Does greater police funding help catch more murderers?

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Abstract

This paper examines the impact of police funding on the fraction of homicides that are cleared by arrest. Using data covering homicides in approximately 50 of the largest US cities from 2007 to 2017, I find no evidence that greater police funding resulted in higher homicide clearance rates. This finding is robust to linear regression and instrumental variable approaches, different ways to measure police budgets, and across victims of different races and in different types of neighborhoods. In summary, the way large city police departments have historically spent their funds, more funding has not helped catch more murderers.

KEYWORDS

arrests, clearance rates, defund police, homicide, instrumental variables, murder victims, police funding

INTRODUCTION

After the killing of George Floyd by Minneapolis Police Officer Derek Chauvin in May 2020, large protests erupted in many American cities. These protests were the culmination of many years of concern and outrage regarding a view that law-enforcement officers have been overly violent and aggressive in policing small infractions of Black and Latino individuals.[1] But there has also been

[1]There are also a variety of studies reflecting some truth behind these views, including Anwar and Fang (2006), Antonovics and Knight (2009), Gelman et al. (2007), Fagan et al. (2012), Horrace and Rohlin (2016), Coviello and Persico (2015), Gonclaves and Mello (2021), and Hoektra and Sloan (2022), just to name a few.

another voice of concern about something arguably just problematic, though less often expressed, which is the perception law-enforcement under-performs when it comes to holding perpetrators responsible for violent crimes such as murder, particularly when the victims are Black and Latino men. In her book *Ghettoside*, the journalist Jill Leovy states:

> Forty years after the civil rights movement, impunity for the murder of black men remained America's great, though mostly invisible race problem. The institution of criminal justice, so remorseless in other ways in an era of get-tough sentencing and "preventative" policing, remained feeble when it came to answering for the lives of black murder victims. (Leovy, 2015, p 7)

This study takes a detailed look at this issue in urban America, examining how the fraction of homicides for which an arrest is made (hereafter referred to as the homicide *clearance rate*) not only varies by the characteristics of the victim, but also how such rates vary across cities conditional on the characteristics of the victim. Of specific interest will be to assess the extent to which city police budgets impact homicide clearance rates. This latter issue is of particular import given one of the most visible calls for action coming from protests in the summer of 2020 was to "Defund the Police." While it was not always well-specified what was meant by defunding the police, many city leaders responded to these calls by saying they would cut their police budgets. Over the course of the 2020, numerous prominent cities as Austin, New York City, San Francisco, Portland, Philadelphia, Baltimore, and Washington, DC all suggested they would make significant cuts to their police budgets. This study hopes to shed some light on the potential consequences of such budget moves when it comes to solving homicides.

To look at these issues, I employ a dataset collected by the Washington Post (Washington Post, 2018), which contains information regarding all homicides that took place in 50 of the largest American cities between 2007 and 2017. These data generally include age, race, and sex of the victim, along with the city and place within the city where the victim was found. I supplement the Washington Post homicide data with city and neighborhood economic and demographic data from the American Community Survey to further assess how homicide clearance rates vary by city and neighborhood characteristics. I then use city budget data to assess the impact of police budgets on homicide clearance rates.

Consistent with previous studies, the data I use here reveal that the mean homicide clearance rate across large American cities during this time period hovered around 60%. Well over half of homicides in these large cities over this time period comprised minority adult males murdered in a heavily minority neighborhood, and moreover, the clearance rate for homicides for such homicides are generally 15–30 percentage points lower than they are for adult White

male victims, adult female victims of all races, and child and elderly victims of all races and gender. There is also substantial variation in homicide clearance rates across cities, with the top five cities clearing over 75% of homicides over this time period, while in the bottom five cities clear less than 45% of homicides.

More specific to this study, I find that while per capita police budgets also vary quite widely across cities, and across years within cities, I find no evidence that such variation has any significant empirical relationship with homicide clearance rates. This result is quite precisely estimated and is robust to controlling for city level, neighborhood level, and victim level characteristics, including recent homicide and unemployment rates, as well as city fixed-effects. Moreover, to control for the potential endogeneity between police budgets and current and expected crime conditions, which could also impact clearance rates, I employ an instrumental variables (IV) approach, where I instrument for city police budgets with contemporaneous city fire protection budgets. These IV results further reveal no evidence that greater police budgets increase homicide clearance rates.

Overall, while this study is not able to directly determine what would happen to homicide clearance rates if large US cities were to dramatically cut or increase their police budgets, the results reveal that over the last decade, variation in police budgets across and within large American cities have had no discernable impact on homicide clearance rates.

RELATED LITERATURE

One of the concerns raised about "Defund the Police" movement is the extent to which taking such actions might harm public safety. A variety of studies provide data regarding this concern indirectly by examining the causal impact of more police officers on crime rates (Chalfin et al., 2022; Chalfin & McCrary, 2018; DiTella & Schargrodsky, 2004; Draca et al., 2011; Evans & Owens, 2007; Klick & Tabarrok, 2005; Levitt, 2002; Mellow, 2019). Overall, these studies have found pretty consistent evidence that, all else equal, increasing the number of police officers lowers crime, particularly violent crime. Arguably, to the extent to which lowering police budgets will lessen the number of police officers, this is also at least suggestive that lowering police budgets will lead to more crime. Indeed, Kaplan and Chalfin (2019) provide evidence for this.

A separate, but arguably just as important concern however, is how lowering police funding may impact homicide clearance rates. Clearance rates, and homicide clearance rates in particular, are a key metric of policing for a couple of reasons. First, effective deterrence requires that those who are considering breaking a law to expect that there will be a reasonable chance that they will face significant consequences if they do so (Becker, 1968; Erlich, 1973; D. Lee & McCrary, 2017). Detecting and charging a large fraction of individuals who

break a law is obviously a key component of this. Given the egregious and irreversible nature of homicide, deterring this particular crime is of foremost interest. Second, almost any notion of justice requires those who break societal rules and harm others are held accountable in some manner. Finding and arresting those responsible for killing others is therefore a necessary component of a just society. Third, as alluded to in the introduction, several journalists have expressed concerns that homicide clearance rates are particularly low when the victims are Black and Latino men. For example, journalist Jill Leovy states "(i)n Jim Crow Mississippi, killers of black people were convicted at a rate that was only a little lower than the rate that prevailed half a century later in L.A.—30 percent then versus 36 percent in Los Angeles County in the early 1990s" (Leovy, 2015).

While to my knowledge there have not been any studies formally looking at the impact of police budgets and crime clearance rates directly, one part of Chalfin et al.'s (2022) analysis looks at the impact of more officers on homicide clearance rates. They find no evidence that more officers have any impact on homicide clearances, both overall and by race of victim. The analysis below differs from Chalfin et al.'s (2022) in a number of ways. Most notably, the analysis below considers the relation of overall city police spending, not police officers, on homicide clearance rates, and maybe even more importantly, I am able to control for victim characteristics such as race, sex, age, and neighborhood demographics of where the victim was found. This is important, as discussed and shown below, there are large differences in clearance rates based on victim characteristics.

While there is not much literature on the relationship between police budgets and homicide clearance rates, there does exist a relatively robust discussion of clearance rates more generally in the criminology literature. One of the most notable trends this literature has documented has been how homicide clearance rates have been declining in the United States over time, from roughly 90% in 1960 to about 60% in the 2000s (FBI, 2007; Ousey & Lee, 2010; Riedel & Jarvis, 1999).

Not surprisingly, such clearance rates differ substantially across cities (Borg & Parker, 2001; Horvath et al., 2001; Keel et al., 2009; Roberts, 2015), across neighborhoods within cities (Mancik et al., 2018; Petersen, 2017), and across different types of crimes, victims, and circumstances (Addington, 2006; Cook et al., 2019; C. Lee, 2005; Litwin & Xu, 2007; Regoeczi et al., 2020; Roberts, 2007; Wellford & Cronin, 1999).

One of the biggest constraints to clearing homicides is the willingness of witnesses to come forward. Such resistance is generally more prevalent in neighborhoods characterized by high levels of social disadvantage (low income, low employment, low education), where residents are often less willing to cooperate with police due to lack of engagement with the community (Regoeczi & Jarvis, 2013), distrust in police (Brunson & Wade, 2019; Desmond et al., 2016;

Litwin, 2004; Puckett & Lundman, 2003; Tyler et al., 2015; Tyler & Fagan, 2008), and possibly a sociological structure the discourages reliance on formal institutions to punish violations (Anderson, 1999). Neighborhoods with these characteristics also generally correspond to those with more violence.

Racial differences in homicide clearance rates have also been looked at somewhat extensively, with mixed results (Bachman, 1994; C. Lee, 2005; Wellford & Cronin, 1999). Part of the reason for these mixed results may be related to the issues discussed above, in the sense that it is not clear which other neighborhood, crime, and context variables should be controlled for when looking at racial disparities in homicide clearance rates. Indeed, in one of the most comprehensive studies of racial variation in homicide clearance rates to date, Fagan and Geller (2018) use data from the FBI's Supplementary Homicide Reports to look at all homicides in the United States between 1976 and 2009. They find that homicides with White victims are significantly more likely to be cleared by arrest than homicides with Black victims, but a substantial portion of this disparity can be accounted for by the racial and socioeconomic characteristics of the county where the homicide took place.

METHODOLOGY

The primary question of interest of this study is whether the likelihood that a homicide is cleared by arrest is impacted by the monetary resources available to the investigating police department? Police department resources can potentially impact homicide clearance rates through a couple of channels. Maybe most obviously, greater police resources may facilitate hiring more officers, whether this be patrolmen or investigators, allowing for more manpower on each homicide case, which could help identify and find murderers (Liska et al., 1985). Similarly, more resources could allow for the purchase of more technology and/or paying confidential informants, both of which could also help identify and find more murderers. Indeed, Braga and Dusseault (2016) and Braga et al. (2019) analyze the impact of a specific intervention in Boston in 2012 which increased the number of homicide detectives, added a civilian crime analyst position and an additional Victim-Witness Resource Officer, engaged in additional training and ordered protocols for the Crime Scene Response Unit, and convened monthly peer review sessions for open homicide investigations. These studies found that the collection of these initiatives involved in this intervention notably increased homicide clearance rates in a city which had historically lagged on this dimension.

There is also a potential indirect impact. Namely, increased police budgets may allow for hiring more police or other types of investments that reduce the number of homicides, which in turn means the homicide detectives and others involved in homicide policing are less capacity constrained, which in turn raises homicide clearance rates.

On the other hand, it has also been argued that while hiring more officers indeed lowers crime, it also increases arrests for low-level crimes, particularly among Black residents (Chalfin et al., 2022). This in turn can create tensions and distrust between community members and police, potentially making community members more hesitant to cooperate and assist with homicide investigations, lessening the ability of police to identify and find murderers. Furthermore, it is by no means clear that additional police resources go to the types of initiatives included in the Boston intervention discussed earlier. Rather, they may far more often be to be used for things that have little relation to solving homicides, such as new cars, better protective equipment, updated facilities, higher salaries, or initiatives to deal with other issues such as homelessness or auto theft.

So how to evaluate whether greater policing resources systematically helps increase homicide clearance rates? As a starting point, one could think of simply comparing the likelihood homicides are cleared across cities that differ in their police spending but are otherwise similar, via a regression of the form:

$$Cleared_{i,c,t} = \alpha + \beta_1 Police\ Budget_{c,t} + \gamma X_{c,t} + \tau_t + \varepsilon_{i,c,t}, \quad (1)$$

where $Cleared_{i,c,t}$ is an indicator for whether or not homicide i in city c in year t was cleared, $Police\ Budget_{c,t}$ is the per capita police budget in city c in year t, $X_{c,t}$ is a vector of demographic and economic characteristics for city c in year t, τ_t capture year fixed-effects (which may capture things like changing technology), and $\varepsilon_{i,c,t}$ is idiosyncratic error. The coefficient β_1 would obviously be our coefficient of interest regarding the impact of police budget size on homicide clearance rates.

However, as was discussed in Section 2 and will be made clear later in this paper, homicides seem to systematically differ in terms of their likelihood of being cleared based on the characteristics of the victim. Most notably, homicides of minority adult males in heavily minority neighborhoods generally have much lower clearance rates than homicides involving nonminority females, or those of children or the elderly. One might argue that homicides are homicides, and police should ensure that the likelihood of clearance should not depend on characteristics of the victim. However, it may truly be that homicides involving adult male minority victims often have circumstances that make them harder to solve than homicides involving females, elderly, or child victims (for example, the latter are often involve family member perpetrators, while the former may be more likely to arise due to gang and/or drug disputes). To the extent that homicides in some cities are disproportionately minority adult males in heavily minority neighborhoods, and those cities spend more money on policing, this may obscure any relation between police budgets and clearance rates. To deal with this, we might want to estimate a regression of the form:

$$Cleared_{i,c,t} = \alpha + \beta_1 Police\ Budget_{c,t} + \gamma X_{c,t} + \varphi Z_i + \tau_t + \varepsilon_{i,c,t}, \quad (2)$$

where everything is the same as in Equation (1), but now we also control for Z_i which is a vector capturing victim characteristics (age, sex, race) for victim i, as well as the neighborhood demographics in which the homicide of victim i took place.

The issue that remains in Equation (2) is that that there still may be omitted variables regarding each city that influence both homicide clearance rates and police budgets. One potential way to address this is to estimate Equation (2) with city-level fixed-effects instead of city-level time invariant characteristics, or

$$Cleared_{i,c,t} = \alpha + \beta_1 Police\ Budget_{c,t} + \gamma Q_{c,t} + \varphi Z_i + \tau_t + \rho_c + \varepsilon_{i,c,t}, \quad (3)$$

where ρ_c is a vector of indicator variables for each city and $Q_{c,t}$ is a vector of just the time-varying city characteristics. The coefficient on police budgets β_1 would now be primarily identified from variation in police budgets within cities over time, conditional on case characteristics and time-varying city characteristics.

Even with the city fixed-effects and the homicide case controls, one might still be worried about an omitted variable bias with respect to the relationship between police budgets and homicide clearance rates. One example might be something like rising gang violence. This gang problem might not only lead to more murders, but might make these murders more difficult to clear due to reluctance to cooperate due to gang affiliation and/or intimidation, as well as cause cities to increase their police budgets. Similarly, policing scandals may reduce police budgets, but also be reflective of poor policing cultures which impact homicide clearance rates.

The above issues suggest that the β_1 estimated from the simple "selection on observables" model, and even city fixed-effect model, via specifications such as those outlined above might not actually identify the impact of police budgets on homicide clearance rates. An oft-used way to overcome such an endogeneity issue is via an instrumental variables (IV) approach. As is well known, key to such an approach is to find a variable that is strongly correlated with the causal variable of interest (in this case city police funding), but conditional on the other included control variables, such a variable can credibly be excluded from having any direct relationship with the outcome of interest (homicide clearance rates). In other words, it must be plausible to assume that any correlation between the instrumental variable and the outcome of interest must only come through the correlation between the instrument and the causal variable of interest. Given such an instrument or instruments, one can then unbiasedly estimate the parameter β_1 in Equation (1) via two-stage least squares (2SLS).

The primary instrument for city police expenditure that I employ is city fire protection expenditure. This instrument is similar to that used by Levitt (2002) in his well-known reanalysis of the impact of police officers on crime, the

difference being he instruments for the number of police officers with the number of fire fighters. Kaplan and Chalfin (2019) also employ a version of this instrument, but instead of instrumenting for the number of police with the number of firefighters, they instrument for police spending with spending on fire protection—as done here. The motivation is identical however, which is that there are a variety of political and institutional reasons why police budgets and fire budgets in a given city might be highly correlated, such as the power of local public sector unions (particularly those dealing with public safety), variation across cities and time in citizen preferences for public safety investments, political posturing regarding what is being done about public safety in the community. On the other hand, one might argue that this variation in police spending that is correlated with fire protection spending is unrelated to local trends in crime, and especially unrelated to what is going on with homicide clearance rates. Hence, the argument is that police spending and fire spending are strongly correlated, but the part of police spending that is correlated to fire spending is plausibly orthogonal to other unobserved things that could impact homicide clearance rates.

As Kaplan and Chalfin (2019) discuss, however, there is a concern that spending on police and fire safety could both be related to a "safety first" regime that encompasses a variety of policy changes responding to an uptick in violence. However, in the analysis below, I control for recent homicide rates, so this concern seems more mitigated. What would invalidate this instrument is if these safety first regimes that impact both police spending and fire spending are specifically responding to an increase in just a particular type of homicides that are harder to clear. While possible, I argue that this does not seem likely.

DATA

The key data for this project come from the Washington Post Homicides dataset (Washington Post, 2018). This dataset contains information on homicides that occurred in 50 of America's largest cities from 2007 through 2017. These data were collected directly from city police departments. In cases when departments did not provide complete information, the data were supplemented with public records (including death certificates), court records, and medical examiners reports.

In the Washington post data, as well as for this study, a homicide refers to murder and nonnegligent manslaughter, but does not include suicides, accidents, justifiable homicides, and deaths by negligence. I also exclude the mass shooting events that appear in the data that I can identify.[2] A homicide is considered

[2]I obtained mass shooting information from https://en.wikipedia.org/wiki/List_of_mass_shootings_in_the_United_States

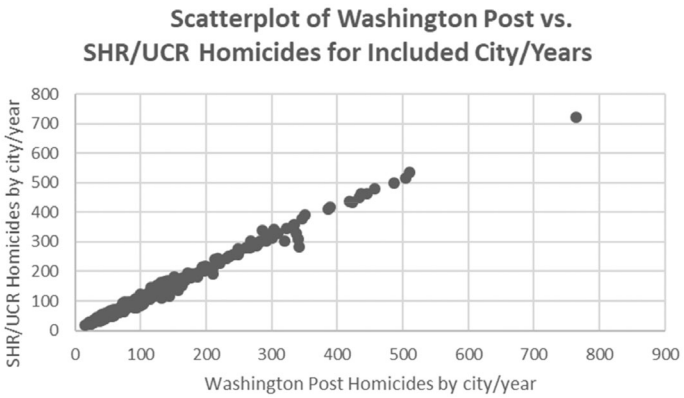

FIGURE 1 Scatterplot of Washington post vs. SHR/UCR homicides for included City/years

"cleared" if the police reported that an arrest was made with respect to that homicide, or if the case was closed because police determined there was sufficient evidence to make an arrest but an arrest was not possible due to death of suspect.

One question is how comprehensive these Washington Post data are in terms of the homicides included. To assess this, I compared the number of homicides in each city–year from the Washington Post data to the Supplementary Homicide Reports (SHR) data (United States Federal Bureau of Investigation, 2020). The SHR contains data on homicides from local police offices reported to the FBI. However, not all cities report data under the SHR program (e.g., cities in Florida). For the handful of cities that do not report homicides under the SHR program, I obtain homicide data from the Uniform Crime Reports (UCR) program via Jacob Kaplan's excellent interactive posting of these data.[3]

To ensure that I am using a relatively comprehensive sample of homicides for each city–year, I limit my sample of homicides to those that occurred in city–years in which the number of homicides reported in the Washington Post data is within 25% of the homicides reported in the SHR/UCR data. This removes homicides from 30 city–years and leaves me with the homicides that occurred in 459 city–years. Figure 1 shows a scatter plot of the number of homicides reported in the Washington Post data versus the SHR/UCR data for each included city–year. As can be seen, these data line up remarkably closely. The correlation coefficient is over 0.99, and if I regress the number of Washington Post homicides for each city–year on the number of SHR/UCR homicides I get a coefficient of 0.96. Given this high correlation, I am relatively confident that

[3]https://jacobdkaplan.com/

for the city–years included in my sample, I am getting an almost complete sample of homicides.

In addition to clearance rate information, for most of the homicides in the Washington Post dataset there is information on race, sex, and age of victim, the date of the homicide, as well as the city where the homicide took place, and the latitude and longitude of the location where the victim was found.[4] I then used this information to map each homicide to a census tract. This allowed me to use data from the Census Bureau's American Community Survey to map racial demographic, income, and poverty data at the city and census tract levels in the year of the homicide to each homicide. However, given the ACS city information for any given year is estimated using sampled data, I worry that much of the variation in city level characteristics across years is largely due to measurement error, especially at the tract level. Hence, I use 2014 5-year averages from ACS data for my measures of city and neighborhood characteristics. This means I do not try to separately control for most city level economic and demographic characteristics when I estimate specifications using city fixed-effects, as these characteristics are fixed within city over time.

For city budget information, I obtained yearly city budget data from the Fiscally Standardized Cities (FiSC) database developed by the Lincoln Institute using data from the U.S. Census Bureau's Annual Surveys of State and Local Governments. This dataset contains annual information on a variety of city budget line items including the amount of city expenditures on Police Protection and Fire Protection. All of these are measured on a per capita basis for each city. These budgets are taken from US Census Bureau data from the quinquennial Census of Government Finance and the Annual Surveys of State and Local Government Finance. These data are available yearly from 1977 to 2017 for over 200 of the America's largest cities, including 49 of the 50 included in the Washington Post homicide data (the one missing city is San Bernardino CA). However, I drop Washington, DC from the sample, as their per capita police expenditures are a significant outlier (over $1000 per capita per year, which is almost double the amount spent at the 90th percentile of the rest of the cities), which is not surprising given they also have duties to cover some of the government buildings and monuments.[5]

One thing to think about is what is the appropriate timing of the budget data that should be applied to each homicide, as it could take some time for allocated policing money to impact actual policing. However, the first thing to note is that these are fiscal data, so they run on the fiscal year from July to June of that year. So, for example, the 2007 fiscal year runs from July 2006 to June 2007.

[4]Given both the Washington Post data and the Census/American Community Survey use the term "Hispanic" when describing ethnicity of Latin American origin, I will subsequently use that term as well.

[5]The mean homicide clearance rate in Washington D.C. between 2007 and 2017 was 0.62, or essentially right at the median across all cities in this dataset over this time period. All of the subsequent results are robust to including homicides in Washington, DC.

Moreover, budget decisions at the city level are generally made at the beginning of the fiscal year, so something like the 2007 policing budget data for a given city primarily reflects decisions made leading up to July 2006. Hence, for a homicide in city c in year y, I assign the police expenditure data associated with city c in fiscal year y. I assign Fire Protection expenditures and overall city spending analogously.

Another issue to consider is whether the correct measure of these budget items is at just the city level, or a broader level that includes things like county level spending that benefits city residents. Given my understanding that most homicides that occur in large cities are under the purview of the city police departments, particularly the detective bureaus in that city police department, it seems most appropriate to use budget information for the city only. However, as a robustness exercise, I will also use the budget data for *FiSCs* as developed by the Lincoln Institute. The Lincoln Institute developed these measures to "provide a full picture of revenues raised from city residents and businesses and spending on their behalf, whether done by the city government or separate overlying governments."[6] These FiSC data allot county level measures on things like policing and fire safety spending, as well as state and Federal government disbursements, to each city based on the city's share of the county population.

To capture local economic conditions, I use Bureau of Labor Statistics to obtain unemployment rates by city and year and assign these to each homicide.[7] Furthermore, to measure the level of segregation in each city, I obtained *isolation indices* for each race/ethnicity for each city from the American Communities Project, which in turn uses U.S. Census data.[8] For a given race/ethnic group, the *isolation index* measures the percentage of same-group population in the census tract where the average member of that group lives. Very low values of this measure for a give race/ethnic group in a given city suggest that members of that group live near many nonmembers of their group, or little segregation of that group from others in that city. By contrast, very high values of this measure for a given group in a given city suggest that most members of this group live in neighborhoods comprised primarily of other members of the same group, or high segregation of this group from others in that city.

After combining these datasets and removing those city–years in which the number of homicides in the Washington Post data differed from the SHR/UCR homicides by more than 25%, I end up with a sample of 48,649 homicides from 47 cities, with 449 city–years represented. A complete list of the cities included and the number of years included for each city is shown in Appendix Table A1.

[6]See https://www.lincolninst.edu/research-data/data-toolkits/fiscally-standardized-cities/explanation-fiscally-standardized-cities for full details.

[7]Technically, I use county level unemployment rates for each year and assign cities an unemployment rate for each year based on the county they are in.

[8]See https://www.brown.edu/academics/spatial-structures-in-social-sciences/diversity-and-disparities for full details.

TABLE 1 Summary of data across cities

	Mean	10th percentile	50th percentile	90th percentile
Washington Post homicide data				
Avg. homicide rate (per 100K) 2007–2017	16.4	7.3	12.3	33.8
Avg. clearance rate	0.6	0.42	0.61	0.76
Lincoln Project City Budget Data (2017 dollars)				
Avg. (per capita) police spending (city only)	$387	$242	$356	$565
Avg. (per capita) police spending (FiSC)	$450	$292	$414	$659
Avg. (per capita) total city expenditures (city only)	$3974	$1773	$3610	$6593
Avg. (per capita) total city expenditures (FiSC)	$7284	$4597	$6924	$9976
ACS data (2014 5-year average)				
Population (000s)	921	260	598	1547
Population percent Black/Hispanic	49.8	27.4	51.4	69.1
Population median HH income	$45,237	$34,002	$45,728	$52,962
Population poverty percent	23	17.7	22.3	30.6
Other city data				
City isolation index (White)	59	43	62	70.5
City isolation index (Black)	50	15	51	80
City isolation index (Hispanic)	34	6	32	61
Avg. unemployment rate	0.07	0.05	0.07	0.09

Table 1 summarizes the key variables from each of these datasets at the city level. As the top row shows, on average, the cities in this analysis had a homicide rate of 16 per 100,000 residents over this time period, but with quite a bit of variation across cities. The second row shows that, when averaged over these years, the mean clearance rate for homicides in the 47 cities included in this sample was about 60%. Though again, there is quite a bit of variation across cities, with some clearing over 75%, with others clearing less than 45%.

The second panel of Table 1 shows that, on average, cities spent about $387 per capita (in 2017 dollars) on policing per year over this time period, though again with considerable variation across cities (this will be discussed in greater detail below). When measured at the FiSC level, this increases to $450 per capita. Though, as discussed above, while county sheriff and other agencies might also provide general policing services to city residents, given homicide investigations are generally handled by city detectives, my preferred budget measure is the city only budget (though I will estimate specifications using both measures to assess robustness). In terms of how big these budgets are compared to overall city budgets, Table 1 shows that, on average, police expenditures are about 10% of overall city expenditures.

The bottom panels describe demographic characteristics of the cities included in this analysis. The fraction Black or Hispanic is higher than the national average, as is the poverty rate. This should not necessarily be surprising as the sample includes only homicides that occurred in large cities, not the surrounding suburbs, smaller cities, or rural areas.

Figure 2a,b describes the distribution of police spending across and within cities in more detail. As can be seen in Figure 2a, the modal amount spent on policing per capita on average over this time period is in the $300–$400 range, but several cities spent in the $400–$600 range. As can also be seen in Figure 2a,

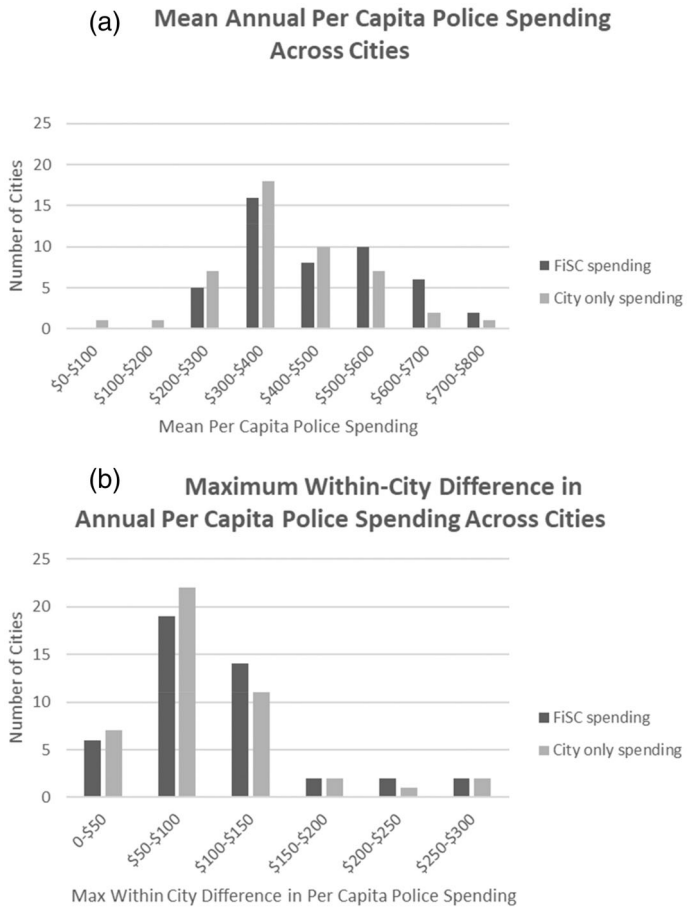

FIGURE 2 (a) Mean annual per Captia police spending across cities. (b) Maximum within-city difference in annual per captia police spending across cities

if using FiSC spending, this distribution shifts right a bit, but still exhibits a good deal of variation across cities.

Figure 2b summarizes the variation in police spending *within* cities between 2007 and 2017, by showing the distribution of the maximal difference across years within cities over these years. Although the modal difference between the maximum and minimum amount spent on per capita policing during this time period within any given city is between $50 and $100, there is again heterogeneity across cities. This is a significant amount given the median city averages $356 per capita on average on police spending in total over this time period.

In terms of homicides and clearance rates, Table 2 summarizes the number of homicides and clearance rates by age, race, and sex, of victim, and neighborhood racial demographics. The first thing to notice is that almost 60% of murder cases in these cities involve minority adult males in census tracts that are majority minority (i.e., tracts that are over 50% Black or Latino). The second thing to notice in Table 2 is that the clearance rate for these homicides that involve minority adult males in census tracts that are majority minority is far lower than it is for any other category, at just 0.47. Notably, by comparison, the clearance rate for minority adult males in census tracts that are majority nonminority is 0.55, and the clearance rate for nonminority adult males in majority minority census tracts is 0.63.

It should also be noted that there is a notable gap in the homicide clearance rate for minority women in majority minority tracts relative to nonminority

TABLE 2 Number of homicides and clearance rates by age, race, neighborhood type, and sex

			Males		Females	
Age group	**Race**	**Neighborhood**	**Number**	**Clearance rate**	**Number**	**Clearance rate**
Adult	Black/Hispanic	Majority minority	26,388	0.47	3225	0.67
Adult	Black/Hispanic	Majority nonminority	3933	0.55	585	0.77
Adult	Not Black/Hispanic	Majority minority	2350	0.63	692	0.70
Adult	Not Black/Hispanic	Majority nonminority	2031	0.71	827	0.83
Elderly	Black/Hispanic	Majority minority	818	0.59	245	0.75
Elderly	Black/Hispanic	Majority nonminority	108	0.69	37	0.89
Elderly	Not Black/Hispanic	Majority minority	322	0.66	139	0.85
Elderly	Not Black/Hispanic	Majority nonminority	337	0.74	215	0.85
Child	Black/Hispanic	Majority minority	921	0.72	456	0.82
Child	Black/Hispanic	Majority nonminority	171	0.84	113	0.88
Child	Not Black/Hispanic	Majority minority	152	0.72	58	0.90
Child	Not Black/Hispanic	Majority nonminority	123	0.85	92	0.88

females. However, clearance rates for females are higher than they are for males across the board. But overall, these findings are certainly consistent with the sentiments expressed in the quote by Jill Leovy shown at the outset of this paper.

Motivated by Table 2, I will categorize homicides into fifteen groups: (1) minority adult males in majority minority census tracts, (2) minority adult males not in majority minority census tracts, (3) nonminority adult males in majority minority census tracts, (4) nonminority adult males not in majority minority census tracts, (5) minority adult females in majority minority census tracts, (6) minority adult females not in majority minority census tracts, (7) nonminority adult females in majority minority census tracts, (8) nonminority adult females not in majority minority census tracts, (9) minority elderly males, (10) nonminority elderly males, (11) minority elderly females, (12) nonminority elderly females, (13) male children, (14) female children, (15) victims for which race, gender, and/or age is missing. As can be seen in Table 2, each of these categories has a reasonable number of observations, and pretty consistent clearance rates within each category. In the regressions that follow, when I say I am controlling for victim/tract characteristics, I include separate indicators for each of these categories.

EVALUATING THE RELATIONSHIP BETWEEN POLICE BUDGETS AND HOMICIDE CLEARANCE RATES

As a very rudimentary look at the connection between homicide clearance rates and police budgets, Table 3 shows the cities with the five lowest and five highest homicide clearance rates over the time period analyzed here. As can be seen, at the bottom end, some cities clear well less than half of their homicides. On the top end, we see that other cities have been able to clear more than three quarters of their homicides. The second column of numbers in Table 3 shows the per capita city police budgets for each of these cities, while the third column shows per capita FiSC police budgets. At a glance, no discernable relationship exists between police budgets and being at the top or the bottom of the homicide clearance rate distribution across cities. The following subsections analyze this relationship in a more rigorous fashion.

OLS regression analysis

Table 4 shows the results of the basic Ordinary Least Squares (OLS) regressions using homicide data aggregated to the city–year level and FiSC level budget data as described by Equations (1)–(3). Column (1) shows the results with just city level control variables and region fixed-effects, column (2) show the results

TABLE 3 Cities with lowest and highest and homicide clearance rates

City	Homicide clearance rate	Avg. city police budget	Avg. FiSC police budget
Bottom five			
Chicago	0.38	$528	$548
New Orleans	0.41	$387	$388
Buffalo	0.42	$328	$367
Baltimore	0.42	$706	$706
Detroit	0.42	$507	$526
Top five			
San Diego	0.76	$272	$364
Tulsa	0.77	$242	$265
Charlotte	0.77	$311	$380
Albuquerque	0.78	$319	$396
Richmond	0.79	$531	$531

when adding further adding controls for victim/tract characteristics, while column (3) shows the results when using just time varying city-level controls (overall city budget, homicide rates, unemployment), controls victim/tract characteristics, and city fixed-effects.

Looking at the top row of coefficients corresponding to the relationship between per capita police budgets and the likelihood a homicide is cleared, we see that in all cases these coefficients are close to zero in magnitude and never statistically positive at any standard level of significance. Focusing on specification (3) which contains city fixed-effects, and has the largest coefficient, suggests that an increase of police spending per capita of $150 (about 1 SD) would be associated with an increase in homicide clearance rates by just over one percentage point. If we consider the 95% confidence interval, we can rule out anything above a 2 percentage point increase in clearance rates associated with increasing per capita police budgets by $100. Note, this is on a mean homicide clearance rate of 60%.

Looking at some of the coefficients on city characteristics in specification (2), it is interesting to note that, while small in magnitude, the coefficient on overall city expenditure is positive in sign and marginally significant, suggesting more overall city spending is associated with higher homicide clearance rates. Not surprisingly, higher recent homicide rates are negatively and significantly correlated with homicide clearance rates.

Table 5 presents some further robustness checks of these basic OLS results. The top two rows simply show again the coefficients on Per Capita Police Spending from columns (2) and (3) from Table 4. The next two rows show the

TABLE 4 OLS regression results—using city-only budget measures

	(1)	(2)	(3)
Per capita police spending ($100s)	−0.015***	−0.010*	0.006
	(0.006)	(0.005)	(0.008)
Per capita total city expenditure ($100s)	0.001**	0.001**	0.001
	(0.000)	(0.000)	(0.001)
City recent homicide rate per 100,000	−0.007***	−0.007***	−0.006***
	(0.001)	(0.001)	(0.001)
Percent unemployed	−0.009**	−0.008**	−0.027***
	(0.004)	(0.004)	(0.005)
City percent Black	0.007***	0.008***	
	(0.001)	(0.001)	
City percent Hispanic	0.000	0.002**	
	(0.001)	(0.001)	
City median HH income ($1000s)	−0.007***	−0.005***	
	(0.002)	(0.002)	
City percent poor	−0.006*	−0.002	
	(0.003)	(0.003)	
City White isolation index	0.003***	0.004***	
	(0.001)	(0.001)	
City Black isolation index	−0.005***	−0.005***	
	(0.001)	(0.001)	
City Hispanic isolation index	−0.000	−0.000	
	(0.001)	(0.001)	
City population (in hundreds of thousands)	0.000	0.000	
	(0.001)	(0.001)	
Victim/tract controls		Yes	Yes
Region indicators		Yes	
City fixed effects			Yes
Year fixed effects	Yes	Yes	Yes
Observations	48,649	48,649	48,649
City–years[a]	449	449	449
R^2	0.053	0.089	0.106

[a]Heteroskedastic robust SEs clustered at city–year level shown in parentheses.
*Indicates significance at the 10 percent level, **indicates significance at the 5 percent level, ***indicates significance at the 1 percent level.

coefficients on Per Capita Police Spending from analogous regressions to those in columns (2) and (3) from Table 4, but using the FiSC measures of police spending rather than the city-only measures used in Table 4. The next panel

presents analogous coefficients to those in the top panel, but estimates these via a probit model rather than OLS since the outcome variable (i.e., whether a homicide was cleared) is a binary variable (marginal effects evaluated at the mean of other variables are shown).

Given the variable of interest (i.e., police budgets) is a city-level treatment, the next panel shows the results after aggregating the data to the city–year level with the dependent variable being the overall homicide clearance rate for each city–year. In practice, the primary difference between these aggregated specifications and those in Table 4 is essentially weighting. The aggregated data are obviously at the city level, so these results are telling us the impact for the average

TABLE 5 Robustness of OLS results[a]

Specification	Budget measure	Control variables	Obs. level	Coefficient on per capita police budget ($100s)	SE
OLS	City only	Hom./Unemp. Rates, City Char., Region F.E.	Individual homicide	−0.010*	0.005
OLS	City only	Hom./Unemp. Rates, City F.E.	Individual homicide	0.006	0.008
OLS	FiSC	Hom./Unemp. Rates, City Char., Region F.E.	Individual homicide	0.002	0.005
OLS	FiSC	Hom./Unemp. Rates, City F.E.	Individual homicide	0.008	0.007
Probit	City only	Hom./Unemp. Rates, City Char., Region F.E.	Individual homicide	−0.010*	0.006
Probit	City only	Hom./Unemp. Rates, City F.E.	Individual homicide	0.007	0.008
OLS	City only	Hom./Unemp. Rates, City Char., Region F.E.	Aggregated to city–year	−0.004	0.010
OLS	City only	Hom./Unemp. Rates, City F.E.	Aggregated to city–year	0.006	0.012
OLS	City only	Unemp. Rates, City Char., Region F.E.	Individual homicide	−0.027***	0.006
OLS	City only	Unemp. Rates, City F.E.	Individual homicide	−0.008	0.009

[a]All specifications control for victim race/age/tract demographic dummies. Heteroskedastic robust SEs clustered at city–year level for homicide level data analyses, at city level for city–year level analyses. For IV Probit results, marginal effects calculated at the mean are shown.
*Indicates significance at the 10 percent level, ***indicates significance at the 1 percent level.

city, while the individual homicide level data are telling us the impact for the average homicide. Regardless, the coefficients are similar to the original specification, generally small in magnitude and never statistically positive at any standard significance level.

The bottom panel is analogous to the top, but excludes homicide rates from the control variables. As can be seen, this causes the coefficient to become larger in absolute magnitude and statistically different from zero in the negative direction. However, this likely seems due to omitted variable bias—higher homicide rates likely cause investigators to become more capacity constrained and may increase overall police budgets. When using city fixed-effects, the coefficient falls again to be not statistically different from zero.

2SLS regression analysis

As described in Section 3, there is a notable endogeneity concern. Police budgets in a given city might be reacting to current or expected future crime issues, which may themselves impact clearance rates (even after controlling for homicide rates). Hence, simple OLS type analysis, even with city fixed-effects, may not accurately identify the impact of police budgets on homicide clearance rates. An arguably superior approach to the OLS specifications discussed above is to exploit variation in police budgets due to factors that have nothing to do with current or expected crime conditions, and see if such variation is correlated with homicide clearance rates. In other words, as discussed in Section 3, in this Section 5.1 take an instrumental variables approach, using Two Stage Least Squares (2SLS) to analyze the impact of police budgets on the likelihood a homicide is cleared.

Key to this approach is to find an instrument that is correlated with city police budgets, but should have no direct relationship with homicide clearance rates other than through how they correlate with police budgets. As discussed previously, the primary instrument I employ here are the amount of money (per capita) each city budgets for fire protection as motivated by Levitt (2002) and also used by Kaplan and Chalfin (2019).

Table 6 presents the 2SLS results. Column (1) shows the first-stage results when using per capita expenditures on fire protection as the instrument for per capita police spending, and controlling for city-level characteristics, region fixed-effects, and controls for victim/tract characteristics. As can be seen, the coefficient on hundreds of dollars of per capita fire spending is statistically positive at the 1% level and the *F*-stat on the significance of this excluded instrument is 14.75, which is also significant at the 1% level and consistent with the Stock–Yogo suggestions for a single instrument for a single endogenous regressor (Stock & Yogo, 2005). The coefficient value of 0.80 suggests that conditional on all the other included control variables, an additional $100 of per capita fire protection spending in associated with about $80 higher per capita police spending.

TABLE 6 2SLS regression results—using city-only budget measures

	First stage (1)	2SLS (2)	First stage (3)	2SLS (4)
Per capita fire spending ($100s)	0.796***		0.483***	
	(0.080)		(0.126)	
Per capita police spending ($100s)		−0.007		−0.029
		(0.012)		(0.033)
Per capita total city expenditure ($100s)	0.013***	0.001**	0.025***	0.001
	(0.003)	(0.000)	(0.006)	(0.001)
City recent homicide rate per 100,000	0.020***	−0.007***	0.029***	−0.004***
	(0.008)	(0.001)	(0.010)	(0.001)
Percent unemployed	0.139***	−0.007*	0.032	−0.026***
	(0.040)	(0.004)	(0.036)	(0.005)
City percent Black	0.002	0.009***		
	(0.009)	(0.001)		
City percent Hispanic	0.027***	0.002*		
	(0.010)	(0.001)		
City median HH income ($1000s)	0.060***	−0.006***		
	(0.015)	(0.002)		
City percent poor	0.107***	−0.004		
	(0.029)	(0.003)		
City White isolation index	0.024***	0.005***		
	(0.009)	(0.001)		
City Black isolation index	0.022***	−0.005***		
	(0.007)	(0.001)		
City Hispanic isolation index	−0.006	−0.000		
	(0.007)	(0.001)		
City population (in hundreds of thousands)	0.023***	0.000		
	(0.006)	(0.001)		
Victim/tract composition controls	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes		
City fixed effects			Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
F-stat on excluded instrument	14.75***		13.94***	
Observations	48,649	48,649	48,649	48,649

(Continues)

TABLE 6 (Continued)

	First stage (1)	2SLS (2)	First stage (3)	2SLS (4)
City–years[a]	449	449	449	449
R^2	0.649	0.088	0.912	0.105

[a]Heteroskedastic robust SEs clustered at city–year level.
***Indicates significance at the 1 percent level.

Column (2) shows the 2SLS results regarding the impact of police budgets on the likelihood a homicide is cleared when using per capita expenditures on fire protection as in instrument for per capita police budgets and controlling for city-level characteristics, controls for victim/tract characteristics, and region fixed-effects. As can be seen, the 2SLS coefficient on (per capita) police spending (in $100s) is effectively zero and is not statistically significant at any standard levels of significance.

Columns (3) and (4) show analogous results to those discussed above, but where I use city-fixed effects in lieu of time fixed city-level control variables and region fixed-effects. Intuitively, this specification is exploiting variation of police and fire protection budgets within cities over time to estimate β_1. Column (3) shows the first-stage, which shows again that the instrument is significantly and positively related to police budgets even with city fixed-effects, with a coefficient of 0.48. The *F*-stat on the excluded instrument remains statistically significant at the 1% level with a value of just under 14. Column (4) shows the 2SLS results when using city-fixed effects. As can be seen, the coefficient on police budgets is still negative in sign and not statistically significant.

Over both specifications, the 95% confidence interval rises to a high of 0.025, meaning we can pretty confidently say that an increase of $100 in per capita police spending increases homicide clearance rates by less than 2.5 percentage points.

Table 7 shows robustness results with respect to the 2SLS results. The top two rows simply show again the coefficient on police spending from columns (2) and (4) of Table 6. The next two rows show the analogous 2SLS results but when using FiSC budget measures rather than the city-only budget measures from Table 6. The next two rows show the results from an IV Probit specification rather than OLS. The next two rows show the results after aggregating the data to the city–year level and using homicide clearance rates as the dependent variable. Once again, almost all of these coefficients are small in magnitude and never statistically significant. The final two rows show the results from analogous regressions to those in the top two rows but excluding homicide rates as control variables. Again, this causes the coefficients to grow in magnitude, but become significantly negative. This is a bit surprising given these are 2SLS results exploiting changes in police budgets associated with changes in fire

TABLE 7 Robustness of two-stage least squares (2SLS) results[a]

Specification	Budget measure	Control variables	Obs. level	Coefficient on per capita police budget ($100s)	SE
2SLS	City only	Hom./Unemp. Rates, City Char., Region F.E.	Individual homicide	−0.024	0.022
2SLS	City only	Hom./Unemp. Rates, City F.E.	Individual homicide	−0.045	0.036
2SLS	FiSC	Hom./Unemp. Rates, City Char., Region F.E.	Individual homicide	−0.007	0.012
2SLS	FiSC	Hom./Unemp. Rates, City F.E.	Individual homicide	−0.029	0.033
IV Probit	City only	Hom./Unemp. Rates, City Char., Region F.E.	Individual homicide	−0.026	0.025
IV Probit	City only	Hom./Unemp. Rates, City F.E.	Individual homicide	−0.042	0.038
2SLS	City only	Hom./Unemp. Rates, City Char., Region F.E.	Aggregated to city–year	−0.043	0.029
2SLS	City only	Hom./Unemp. Rates, City F.E.	Aggregated to city–year	−0.013	0.037
2SLS	City only	Unemp. Rates, City Char., Region F.E.	Individual homicide	−0.070***	0.018
2SLS	City only	Unemp. Rates, City F.E.	Individual homicide	−0.068**	0.030

[a]All specifications control for victim race/age/tract demographic dummies. Heteroskedastic robust SEs clustered at city–year level for homicide level data analyses, at city level for city–year level analyses. For IV Probit results, marginal effects calculated at the mean are shown.
**Indicates significance at the 5 percent level, ***indicates significance at the 1 percent level.

protection budgets. One explanation could be that higher homicide rates not only congest investigators, but also may increase budgets for protective services such as fire departments.

Overall, the results from the 2SLS specifications reveal no evidence that increases in police budgets increase homicide clearance rates.

Results by race

Table 8 presents the key results separated by race of the victim and type of neighborhood in which the victim was found. We can look first at the top panel,

TABLE 8 OLS and 2SLS results by race and neighborhood type[a]

Group	Specification	Control variables	Coefficient on per capita police budget ($100s)	SE
Black/Hispanic victim	OLS	Hom./Unemp. Rates, City Char., Region F.E.	−0.009*	0.005
Black/Hispanic victim	OLS	Hom./Unemp. Rates, City F.E.	0.001	0.008
Black/Hispanic victim	2SLS	Hom./Unemp. Rates, City Char., Region F.E.	−0.046**	0.022
Black/Hispanic victim	2SLS	Hom./Unemp. Rates, City F.E.	−0.048	0.034
Non-Black/Hispanic victim	OLS	Hom./Unemp. Rates, City Char., Region F.E.	−0.016**	0.007
Non-Black/Hispanic victim	OLS	Hom./Unemp. Rates, City F.E.	0.023	0.015
Non-Black/Hispanic victim	2SLS	Hom./Unemp. Rates, City Char., Region F.E.	−0.107	0.093
Non-Black/Hispanic victim	2SLS	Hom./Unemp. Rates, City F.E.	−0.020	0.061
Maj. Black/Hispanic neighborhood	OLS	Hom./Unemp. Rates, City Char., Region F.E.	−0.005	0.006
Maj. Black/Hispanic neighborhood	OLS	Hom./Unemp. Rates, City F.E.	0.010	0.008
Maj. Black/Hispanic neighborhood	2SLS	Hom./Unemp. Rates, City Char., Region F.E.	−0.023	0.024
Maj. Black/Hispanic neighborhood	2SLS	Hom./Unemp. Rates, City F.E.	−0.048	0.041
Maj. Non-Black/Hispanic neighborhood	OLS	Hom./Unemp. Rates, City Char., Region F.E.	−0.015**	0.006
Maj. Non-Black/Hispanic neighborhood	OLS	Hom./Unemp. Rates, City F.E.	−0.015**	0.006
Maj. Non-Black/Hispanic neighborhood	2SLS	Hom./Unemp. Rates, City Char., Region F.E.	−0.027	0.048
Maj. Non-Black/Hispanic neighborhood	2SLS	Hom./Unemp. Rates, City F.E.	−0.005	0.061

Abbreviations: 2SLS, two-stage least squares; OLS, ordinary least squares.
[a]All specification control for victim race/age/tract demographic dummies. Heteroskedastic robust SEs clustered at city–year level for homicide level data analyses, at city level for city–year level analyses.
**Indicates significance at 5 percent level.

which limits the analysis to only Black/Hispanic victims. The first two rows show the OLS coefficients on police spending for specifications controlling for victim gender and tract demographics, and either city-level controls (first row)

or city fixed-effects (second row). As can be seen, the coefficients are small in magnitude and not statistically positive. The third and fourth rows show the 2SLS results for Black and Hispanic victims when using per capita fire spending as the instrument for per capita police spending, for in specifications controlling for victim gender and tract demographics, and either city-level controls (first row) or city fixed-effects (second row). Again, the coefficients are relatively small in magnitude, actually negative in sign, and not statistically positive.

The second panel of Table 8 shows the analogous results when limited to only non-Black/non-Hispanic victims. Given the much smaller sample size, these coefficients are substantially more imprecisely estimated as can be seen by the much larger SEs. However, the coefficients are again generally negative in sign, and again generally not statistically significant.

The bottom two panels show the result for homicides in majority minority tracts and homicides in majority nonminority tracts respectively. Once again, the coefficients are negative in sign and generally small in magnitude.

Overall, the results in Table 8 do not reveal any consistent heterogeneities by race or neighborhood type with respect to the impact of police budgets on homicide clearances. Moreover, again this table provides no evidence that that greater police budgets increase homicide clearances.

DISCUSSION

As discussed throughout, the above results provide no evidence that greater police budgets lead to increases in homicide clearance rates (or equivalently, lower police budgets decrease homicide clearance rates). On the one hand, this might not be very surprising, as police budgets can be used for many things—more patrol officers, officer salary increases, new technology, new capital expenditure, even car upgrades—most of which would not be expected to increase homicide clearance rates. Therefore, one question is whether greater police resources are related to things that would potentially impact homicide clearance rates, notably more investigators, particularly homicide investigators.

While I do not know of data that measure the number of homicide detectives in each police department, the Law Enforcement Management and Administration Statistics (LEMAS) data (United States Department of Justice, 2011, 2015, 2020) measures not only how many sworn officers in each police department, but also the number of investigators (of all kinds). One constraint of these data, however, is that it is not measured every year. Indeed, during the 2007–2017 period analyzed here, the LEMAS only covers 2007, 2013, and 2016. However, this is enough to at least look at the relationship between changes in police budgets and changes in the number of officers and changes in number of investigators. Before proceeding though, it should be noted that, as Chalfin and McCrary (2018) discuss, there is substantial measurement error when it comes

to measuring the number of officers in each department when using the Uniform Crime Reports. Given that the LEMAS data are collected via a similar type survey to the UCR data, such measurement error likely arises here as well, which could lead to substantial attenuation bias toward zero. Therefore, the results below should be taken with a grain of salt.

Table 9 shows some summary statistics for the LEMAS data. As can be seen, investigators usually appear to make up about 20% of the total number of sworn officers.

To look at whether changes in police budgets seem to impact the number of investigators in each city, I estimate a regression of the following form:

$$N_{c,t} = \alpha + \beta_1 Police\ Spending_{c,t} + \rho_c + \tau_t + \varepsilon_{c,t},$$

where $N_{c,t}$ is the number of investigators per 1000 population in city c in year t (or the total number of sworn officers per thousand population in city c in year t in other specifications), $Police\ Spending_{c,t}$ is again the per capita budget (in 100s of 2017 dollars) for police in city c in (fiscal) year t, ρ_c captures city fixed-effects for each city c, τ_t captures fixed-effects for each year t, and $\varepsilon_{c,t}$ captures idiosyncratic error. I estimate this specification both via OLS and 2SLS, where again spending of fire protection is the *excluded* instrumental variable. I also estimate analogous specifications using the natural log of the number of investigators (total sworn officers) as the dependent variable and the natural log of police spending as the key right-hand side variable. This roughly captures the elasticity of the number of investigators (total officers) with respect to changes in police budgets. In all specifications, SEs are clustered by city.

The results of these regressions are shown below in Table 10. While most of the coefficients in this table are not statistically significant, there are some things to note. First looking at the OLS results, the coefficients on the police budget variables are substantially larger when it comes to the number of investigators relative to the total number of officers. Indeed, when looking the log–log specifications in column (2), the point estimate of the estimated elasticity is six-times greater when it comes to investigators than overall officers. Indeed, this

TABLE 9 Summary statistics of Law Enforcement Management and Administration Statistics (LEMAS) data for included cities

	Mean	10th percentile	50th percentile	90 percentile
Total sworn officers/1000 pop	2.64	1.55	2.49	4.11
Total investigators/1000 pop	0.46	0.24	0.42	0.69
Number of city–years	115			
Number of cities	47			

TABLE 10 Regression results—police personnel on police spending[a]

	OLS		2SLS	
	Dep Var: Investigators/1000 pop		Dep Var: Ln[Investigators/1000 pop]	
	(1)	(2)	(3)	(4)
Per capita police spending ($100s)	0.07		0.17	
	(0.04)		(0.12)	
Ln[Per capita police spending]		0.65*		2.69
		(0.37)		(1.91)
	OLS		**2SLS**	
	Dep Var: Tot. Officers/1000 pop		**Dep Var: Ln[Tot. Officers/1000 pop]**	
Per capita police spending ($100s)	−0.02		0.38	
	(0.13)		(0.44)	
Ln[Per capita police spending]		0.06		0.44
		(0.15)		(0.48)

Abbreviations: 2SLS, two-stage least squares; OLS, ordinary least squares.
[a]All specifications include city and year fixed-effects. SEs clustered by city.
*Indicates significance at the 10 percent level.

coefficient is marginally statistically significant for investigators (both of the investigator coefficients are statistically significant at the 1% level when I do not cluster SEs).

Looking at the 2SLS results in columns (3) and (4), we again see that none of the coefficients are statistically significant (though again, if I do not cluster SEs by city, the coefficients on police spending in the investigators specifications are significant at the 1% level). However, it is still interesting to at least consider the coefficients. Looking at column (3), the coefficient on police spending is just over twice as large in the total officers specification than the investigators specification, but recall that investigators are generally less than 20% of total officers. This means there is a larger proportional increase in investigators with more (exogenous) police spending than officers overall. This is again revealed in column (4), where in the log–log specification the estimated elasticity of investigators with respect to (exogenous) police spending is over five times higher than the estimated elasticity of total officers with respect to (exogenous) police spending.

In summary, while these estimates are quite imprecisely estimated (and may contain significant measurement error), they are at least suggestive that when police budgets increase (decrease), the number of investigators grows (shrinks), likely to a greater degree than overall officers. This is somewhat

surprising given the earlier results suggesting greater police budgets have little impact on homicide clearance rates. One explanation might be that the key to solving homicides, especially those of minority males in heavily minority communities that generally have the lowest clearance rates, lie outside of standard investigative work. Rather, solving such crimes may have more to do with the local community trust in the police overall (see again discussion and citations in Section 2).

Furthermore, homicide investigators are just a subset of all investigators in a given city's police department. For example, the Los Angeles Police Department Detective Bureau lists six separate detective bureau divisions (Robbery/Homicide/Violent Crimes Division, Forensic Science and Technical Division, Juvenile Division, Gang and Narcotics Division, Commercial Crimes Division, Detective Support and Vice Division). The New York City Police Department Detective Bureau lists over 20 detective squads and divisions (Gang Squad, Homicide Squad, Narcotics Squad, Overdose Squad, Special Victims Division, Forensic Investigations Division, Animal Cruelty Squad, Arson Squad, Cold Case Squad, Computer Crimes Squad, Hate Crimes Task Force, Major Case Squad, Missing Persons Squad, Auto Crime Division, Criminal Enterprise Division, Fugitive Enforcement Division, Central Robbery Division, District Attorneys Squad, Grand Larceny Division, Gun Violence Suppression Division, Vice Enforcement Division). Certainly, it may be the case that when a department gets extra funding, they tend to add detectives to these specialized investigation divisions rather than homicide.

CONCLUSIONS

This paper examined homicide clearance rates in large United States cities over the 2007–2017 period. In doing so, I find that such clearance rates vary significantly both across cities, and within cities based on the neighborhood of the murder and the age and race of the victim. Consistent with previous studies, I find that the likelihood a homicide is cleared by arrest is notably lower when the victim is a Black or Hispanic adult male and the homicide occurred in a more heavily minority neighborhood.

The unique finding to this study, however, is that I find no evidence that greater police budgets increase homicide clearance rates. This finding is robust across a wide variety of regression specifications, including simple OLS regression specifications, Two-stage least squares specifications, and different ways to measure police budgets. Moreover, this finding is also not simply due to lack of precision, as coefficient estimates are generally very small in magnitude and often negative in sign.

It should be clear, however, that these results do not necessarily imply that more police funding is not required to increase homicide clearance rates. Indeed,

the 2012 Boston initiative discussed earlier suggests that more resources can be quite effective for catching more murderers. Rather, the results from this paper simply suggest that the way police departments have generally been using their funding over the last decade plus, more funding has not systematically helped police better find and arrest those responsible for murdering others.

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DATA AVAILABILITY STATEMENT

Data necessary to replicate the results of this article are available upon request from the author.

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APPENDIX

TABLE A1 Cities included in sample

City	Number of years
Albuquerque, New Mexico	6
Atlanta, Georgia	10
Baltimore, Maryland	11
Baton Rouge, Louisiana	6
Birmingham, Alabama	9
Boston, Massachusetts	11
Buffalo, New York	10
Charlotte, North Carolina	11
Chicago, Illinois	10
Cincinnati, Ohio	10
Columbus, Ohio	10
Dallas, Texas	10
Denver, Colorado	7
Detroit, Michigan	8
Durham, North Carolina	8
Fort Worth, Texas	10
Fresno, California	11
Houston, Texas	11
Indianapolis, Indiana	11
Jacksonville, Florida	11
Kansas, Missouri	11
Las Vegas, Nevada	10
Long Beach, California	11
Los Angeles, California	8
Louisville, Kentucky	8
Memphis, Tennessee	11
Miami, Florida	11
Milwaukee, Wisconsin	11
Minneapolis, Minnesota	10
Nashville, Tennessee	11
New Orleans, Louisiana	8
New York, New York	2

(Continues)

TABLE A1 (Continued)

City	Number of years
Oakland, California	10
Oklahoma, Oklahoma	10
Omaha, Nebraska	10
Philadelphia, Pennsylvania	10
Phoenix, Arizona	7
Pittsburgh, Pennsylvania	11
Richmond, Virginia	10
Sacramento, California	10
San Antonio, Texas	8
San Diego, California	11
San Francisco, California	11
St. Louis, Missouri	11
Stockton, California	10
Tampa, Florida	7
Tulsa, Oklahoma	10