

# Conclusions from the history of research into the effects of police force size on crime—1968 through 2013: a historical systematic review

YongJei Lee<sup>1</sup>  · John E. Eck<sup>1</sup> · Nicholas Corsaro<sup>1</sup>

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## Abstract

*Objectives* We describe and explain how the findings from nonexperimental studies of the relationship between police force size and crime have changed over time.

*Methods* We conduct a systematic review of 62 studies and 229 findings of police force size and crime, from 1971 through 2013. Only studies of U.S. policing and containing standard errors of estimates were included. Using the robust variance estimation technique for meta-analysis, we show the history of study findings and effect sizes. We look at the influence of statistical methods and units of analysis, and time period of studies' data, as well as variation in police force size over time.

*Results* Findings vary considerably over time. However, compared to research standards and in comparison to effect sizes calculated for police practices in other meta-analyses, the overall effect size for police force size on crime is negative, small, and not statistically significant. Changes in research methods and units of analysis cannot account for fluctuations in findings. Finally, there is extremely little variation in police force size per capita over time, making it difficult to estimate the relationship with reliability.

*Conclusions* This line of research has exhausted its utility. Changing policing strategy is likely to have a greater impact on crime than adding more police.

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✉ YongJei Lee  
lee2yj@mail.uc.edu

John E. Eck  
john.eck@uc.edu

Nicholas Corsaro  
nicholas.corsaro@uc.edu

<sup>1</sup> School of Criminal Justice, University of Cincinnati, Cincinnati, OH 45221, USA

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## Introduction

Social scientists have demonstrated that some police practices can be effective at reducing crime or disorder. Systematic reviews of hot spots policing (Braga et al. 2014), focused deterrence (Braga and Weisburd 2012), problem-oriented policing (Weisburd et al. 2010), and third-party policing (Mazerolle and Ransley 2006), for example, provide evidence for the relative effectiveness of these strategies. Long before researchers and practitioners conceived of these strategies, police and researchers were asking a far more basic effectiveness question: does hiring more police reduce crime. Two systematic reviews of the impact of police force size on crime have been recently published. Lim and colleagues (2010) count the number of findings that demonstrate a statistically significant crime reduction effect and find that such studies were in the minority of published findings. Even more recently, Carriaga and Worrall (2015) conducted a systematic review of 24 studies and meta-analysis of 12 studies. They found a small but significant crime reduction impact of police force size on crime.

In this paper, we are interested in the development of research over time. We use methods developed for systematic reviews and meta-analysis for this purpose. We are not simply concerned with drawing a conclusion about whether adding police reduces crime, though this is important. We are also interested in how the findings change over time and in uncovering possible reasons for the findings: do changes in methods and data correspond with differences over time, for example.

Our paper builds on prior findings in three specific ways. First, we show how findings have changed over time. These changes are critical for understanding what we know about the police force size–crime relationship. Second, we include all relevant studies identified in our analysis (over 60 studies with over 200 separate findings). This provides a more complete picture of what the research shows. Third, we examine likely explanations for the cumulative research findings. Our inquiry provides insights into how researchers produce knowledge and the impact of their evolving research methods on their findings. In the end, there appears to be no impact on crime in general of hiring more police, and advances in research methods do not seem to have helped to produce stronger conclusions on this important issue.

We organize our paper as follows. Following this introduction, we describe the economic theory of the police production of less crime, and outline the principle difficulties researchers face when trying to test it. In the third section, we describe the methods we use to identify the empirical research linking police force size to crime. The fourth section shows how the findings from this research have fluctuated over time. We first illustrate this change using descriptive findings over time and then we show effect sizes over time. These show contradictory results. The descriptive findings indicate that results have fluctuated over time, but recently the addition of police seems to have had a greater impact on crime. In contrast, the meta-analysis shows that, at least for the last four decades, findings seem to be constant and have no impact on crime reduction. In the fifth section, we test for possible explanations related to these findings: changes in the statistical methods and units of analysis, and the lack of variation in the principle independent variable (i.e., police size stability over time). Based on the tests

of these explanations, we conclude that there is little reason to continue conducting research examining the police force size–crime relationship. However, for cost-conscious mayors, city managers, and city councils, there is a silver lining: modest planned reductions in police force size are unlikely to have a consequential impact with regard to overall crime.

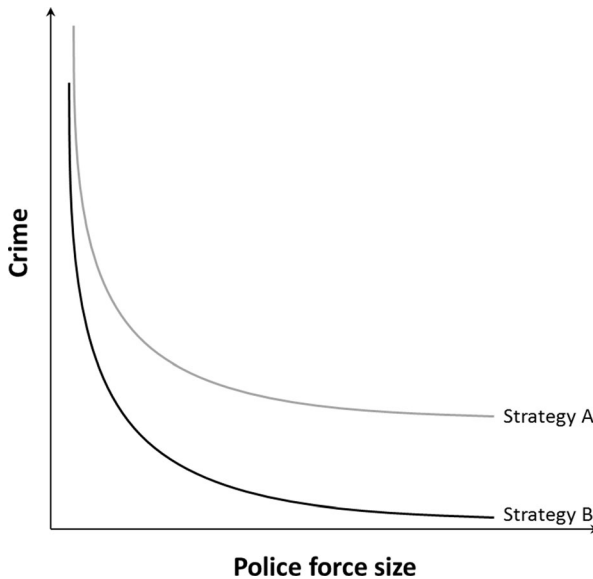
## The hypothesis that more police reduces crime

The hypothesis that increasing police force size reduces crime is relatively simple. It treats a police agency as a “firm” with a single homogeneous input, labor, and set of outcomes that are various forms of crime (Becker 1968). Using the typical *ceteris paribus* argument, as the number of police officers increases, crimes should decline, for a variety of reasons. More police should increase arrests of offenders, some of whom end up incarcerated for their crimes. Thus, one mechanism driving this relationship is incapacitation: what Nagin (2013) refers to as the apprehension role of police. General deterrence is a second mechanism: with more police, potential offenders perceive that their risk of being caught after offending is higher, so they too cut back on their crimes. Nagin (2013) calls this the sentinel role of police. Another possible mechanism is specific deterrence: more police officers allows tracking of specific offenders, who then cut back on their misdeeds. This is a special case of the sentinel role. Nagin, Solow, and Lum (2015) present a theoretical model of policing that suggests that the sentinel role is more effective than the apprehension role, though the two roles are intertwined.

Becker (1968) focuses his attention on the apprehension role; “The more that is spent on policemen, court personnel, and specialized equipment, the easier it is to discover offenses and convict offenders. One can postulate a relation between the output of police and court ‘activity (A)’ and various inputs of manpower (m), materials (r), and capital (c), as in  $A = f(m, r, c)$ , where f is a production function summarizing the ‘state of the arts’.” (p. 174). Though Becker focuses on apprehension, his argument is not dependent on the precise mechanism by which numbers of police produce crime reductions.

Becker (1968) also assumes, following standard economic theory, that there are diminishing marginal returns to policing. That is, as inputs increase, the outputs would increase, but at a declining rate: the benefit of the first 100 officers deployed would be greater than the benefits of the next 100 deployed, which would be greater than the next 100, and so on. We can summarize Becker’s ideas in Fig. 1. The horizontal axis is the number of police, and the vertical axis is the number of crimes. The curves represent the theoretical relationship between these two variables, assuming all other factors influencing crime have been controlled for. The shapes of the curves show the declining marginal utility of police officers.

Historical examples provide evidence that removing police can spark a large increase in crime (the equivalent of moving from the right to the extreme left on the curve). Andenaes (1974) gives two examples—the Liverpool Police strike of 1919, and the Nazi arrest of the Danish police in 1944—where the removal of policing preceded a dramatic surge in crime. Russell (1975 [1930]) describes a similar result from the 1919 Boston police strike (the Finnish police strike of 1976 produced only a small increase in crime and may provide a counter example [Makinen and Takala 1980]). From these



**Fig. 1** Theory of police force size and crime reduction

examples, it is reasonable to conclude that moving from zero police to a modest number of police is likely to reduce crime substantially.

The research we are reviewing does not address this. Rather, it examines whether a small (marginal) change in the size of an existing police force has an impact on crime. In short, it looks at the right part of the curve, rather than the extreme left part where crime drops rapidly with foundational (baseline) changes in police force size.

Becker (1968) notes that “it would be cheaper to achieve any given level of activity... the more highly developed the state of the arts, as determined by technologies like fingerprinting, wiretapping, computer control, and lie-detecting” (p. 174). This too is in keeping with standard economic theory, which assumes that at any given time, a firm is using a particular technology. An improvement in technology shifts the curve downward. In Fig. 1, strategy A is the “older” technology, while strategy B is a “newer” technology. For any given level of police force size, there is less crime with strategy B than strategy A, though both curves show a similar relationship between police force size and crime. Becker (1968) reflects the thinking of the 1960s by focusing on physical technology. Today, we can think of “state of the art” as reflecting the operational strategy of a police department. We will come back to this extremely important point later in the paper.

The first empirical attempt to estimate the relationship between police force size and crime was by Morris and Tweeten in 1971. Controlling for other confounders, they found that an increase in police force size results in an increase in crime. Since this study, there have been numerous other efforts. Two recent systematic reviews suggest contrasting conclusions. Lim and colleagues (2010) claimed there is more evidence contradicting a crime reduction effect of hiring more police than there is evidence supporting it. In contrast, Carriaga and Worrall (2015) suggested there is a small but significant crime reduction effect, on average. This contrast may be due to the criteria for selecting studies and the methods they used to analyze them. Lim, Lee, and

Cuvelier (2010) examined 58 studies. They counted the number of findings supporting and contradicting the crime reduction hypothesis: a vote count analysis. Carriaga and Worrall (2015) restricted the studies they examined to those that analyzed the relationship between police force size and crime over time. They included 24 studies in their systematic review and 12 in their meta-analysis. Nevertheless, reconciling their different conclusions is important. Given that researchers have been examining this topic for over 40 years, it is also important to examine how findings have changed over the past four decades.

## Methods

To systematically assess the relationship between police force size and crime, we followed established systematic review methods (Cook et al. 1997; Higgins and Green 2011; Mulrow and Oxman 1997) and used an advanced meta-regression technique. Our target studies are those that describe an empirical relationship between police force size (or a proxy for this independent variable) and crime, for police agencies in the United States. We restricted the inquiry of our study to the U.S. because most of the studies of this type describe U.S. policing, thus including the small number of non-U.S. studies would increase the heterogeneity in the findings without shedding additional light on the subject. Consequently, we do not make any assertions about the generalizability of our findings to police forces outside the U.S., nor do our findings apply to U.S. Federal law enforcement agencies, as well as county, or state police forces.

## Search strategy

We examined the English-written literature using both electronic and manual searches. Our electronic search of various databases<sup>1</sup> used these keywords: *police force*, *police employment*, *police level*, *police expenditure*, *police budget*, *police effectiveness*, *police hiring*, *COPS* and *GAO* (*Government Accountability Office*), and *police deterrence*. Because the literature on this topic prior to Becker's (1968) economic theory of crime offered few empirical findings, we retrieved studies from 1968 through March 2015. We also conducted manual reference checks of relevant literature, including the two recent systematic reviews described above. Finally, we contacted scholars in this field and asked them about any study we may have missed. We presented an early version of this study at the Annual Conference of the American Society of Criminology at Atlanta, Georgia in 2013, and asked attendees if they knew of gaps in our literature. We relied upon an iterative approach rather than a sequential approach. Once we found studies that met the keywords criteria from a search of online databases, we searched the bibliographies in the new studies for other papers. If new keywords became apparent,

<sup>1</sup> Sociological Abstracts, Social Science Abstracts (SocialSciAbs), Social Science Citation Index, Arts and Humanities Search (AHSearch), Criminal Justice Abstracts, National Criminal Justice Reference Service (NCJRS) Abstracts, Educational Resources Information Clearinghouse (ERIC), Legal Resource Index, Dissertation Abstracts, Government Publications Office, Monthly Catalog (GPO Monthly), Google Scholar, Online Computer Library Center (OCLC) SearchFirst, CINCH data search, and C2 SPECTR (The Campbell Collaboration Social, Psychological, Educational and Criminological Trials Register).

we conducted another on-line search. This was particularly important because the online databases have limited access to studies prior to the 1980s, and because the terminology used has changed over the decades.

### Literature screening and data extraction

We used a three-step screening process to select studies. First, we reviewed both abstracts and tables with empirical findings to determine if a study contained an empirical assessment of the relationship between police force size and crime. We then examined the entire article for all studies that met the step-one criteria. Second, we dropped the studies that did not provide the standard errors of estimated coefficients showing the effect of police force size on some form of crime. Six studies failed to provide this information. Finally, we eliminated any study of policing outside the U.S. Table 1 summarizes these steps. By step three, we had included 62 studies and 229 findings (most studies reported on multiple crime types resulting in multiple findings). A comparison with two other recently published systematic reviews by Lim, Lee, and Cuvelier (2010) and Carriaga and Worrall (2015) suggests that we drew upon a similar but slightly more comprehensive body of studies, despite using slightly different selection criteria (see Table 1).

### Coding protocol

Though the search period for literature was between 1968 and 2015, we found relevant studies between 1971 and 2013. For each finding, we coded whether or not it supported a crime reduction hypothesis (a statistically significant negative relationship between police force size and crime). To meta-analyze the overall effect size of 229 findings across 62 studies, we recorded the standard errors and relevant statistics (e.g., sample size, t-statistics, confidence interval, and standard deviations) for each estimated coefficient linking police force size to crime.

We also coded statistical modeling techniques of the 62 studies over this 43-year period: Ordinary least squares, 2-stage least squares, 3-stage least squares, hierarchical linear modeling, and first-difference generalized method of moments. We also accounted

**Table 1** Number of studies and findings considered for systematic review

	Number of articles	Percent of articles	Number of findings	Percent of findings
Step 1 – empirical studies	70	100	258	100
Step 2 – include standard error	64	91	236	91
Step 3 – U.S. police agencies	62 <sup>a</sup>	89	229	89
Lim et al. 2010 (includes five non-US studies)	58		256	
Carriaga and Worrall 2015 (includes one non-US study)	24 <sup>b</sup> (12)		Not reported	

<sup>a</sup> Appendix A. provides a full list of these studies

<sup>b</sup> Reports 68 relevant studies found

for the year of publication, geographic unit of analysis (city, county, metropolitan area, or state) focused on, and the years from which the data were collected. Table 2 shows the characteristics of the studies reviewed in this paper.

### Descriptive findings over time

Our first interest is to determine whether findings appear to change over time. We are interested in showing how a diligent reader of the police force size literature might view the conclusions of studies as the cumulative findings evolve. Such a reader will not be conducting a progressive meta-analysis, updated with every new study. Rather, she or

**Table 2** Characteristics of the studies analyzed

Characteristics	Number of studies	%	Number of findings	%
Year of publication				
1971–1979	16	25.8	50	21.8
1980–1989	9	14.5	14	6.1
1990–1999	12	19.4	31	13.5
2000–2009	21	33.9	116	50.7
2010–2013	4	6.5	18	7.9
Geographic unit				
City, district, precinct	33	53.2	121	52.8
County	6	9.7	27	11.8
Juris, Sub/SMSA, area	10	16.1	39	17.0
State, nation	13	21.0	42	18.3
Measure of police <sup>a</sup>				
Dollar	24	38.7	82	35.8
Number	37	59.7	143	62.4
Type of analysis				
OLS, BA, VAR	35	56.5	113	49.3
2SLS, 3SLS	22	35.5	91	39.7
HLM, GMM	5	8.1	25	10.9
Control for simultaneity				
Yes	32	51.6	143	62.4
No	30	48.4	86	37.6
Crime reduction hypothesis				
Supportive	32	51.6	83	36.2
Non-supportive	30	48.4	146	63.8
Total	62	100	229	100

*BA* bivariate analysis, *GMM* (first differenced) generalized method of moments, *OLS* ordinary least squares, *2* (or *3*) *SLS* two (or three) stage least squares, *VAR* vector auto regression, *HLM* hierarchical linear modeling

<sup>a</sup> One study (and corresponding four findings) used number of days as a measure of police force

he is likely to count the number of studies that seem to support the hypothesis that more police reduce crime, relative to the studies that fail to support this hypothesis.

There are several serious limitations to such an approach (which we describe shortly), but this approach is probably a reasonable approximation of how researchers and practitioners might alter their views of the hypothesis over time. We began by sorting the 229 findings into two categories: those that support the crime reduction hypothesis, and those that do not. We classified a finding as supportive if there was at least one significant negative coefficient for police force size. Otherwise, we classified it as contradictory. If a study had at least one supportive finding, we coded the study as supportive. Otherwise, we coded it as contradictory. We then, for each year, subtracted the contradictory studies from the supportive studies.

Figure 2 displays the differences between the supporting and contradicting studies over time. It is apparent that the net conclusions have fluctuated a great deal across the study period. Specifically, we find that an equal number of studies had supported and contradicted during the 1970s. However, during the 1980s and 1990s, the number of contradicting studies was two times greater than the number of supporting studies. After 2000, it is apparent that the crime reduction hypothesis became more predominant. Over the entire 43-year period, more studies support the crime reduction hypothesis than contradict it. In conclusion, a diligent reader who had followed this literature over 43 years might change her or his mind several times, but conclude in 2015 that on balance hiring more police seems to have an impact on crime reduction. Not only are there a few more studies supporting this conclusion, since 2000 the research seems to point in this direction.

There are two reasons this analysis may be misleading. First, changing how we count changes our conclusions. If we count findings rather than studies, we find that about 36 % of findings across studies are supportive, while 64 % of findings are not.

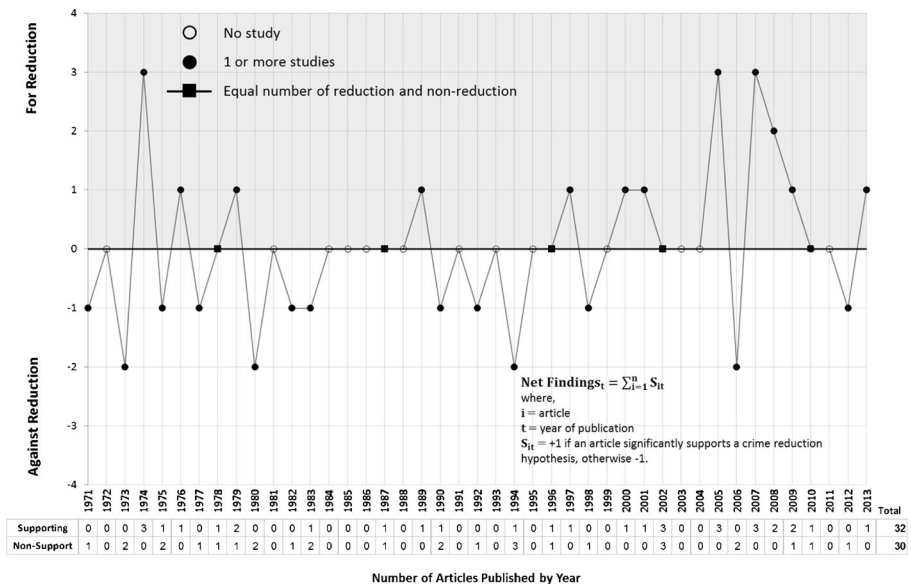


Fig. 2 The fluctuating findings for studies of police force size–crime relationships: 1971 through 2013



This is consistent with Lim and colleagues (2010) who reported 21 % of the findings in their database supported a crime reduction effect of police strength (the other 79 % of the findings were either nonsignificant or significant positive relationships). Second, comparing studies or findings in this way assumes each study (or finding) is equally weighted, thus we are accepting the null hypothesis for nonsignificant findings, rather than concluding we are uncertain of the true finding. In fact, our confidence in findings is dependent on its standard error. We should, therefore, weight findings by their standard errors and compare effect sizes. We next turn to this more precise analysis.

## Statistical analysis

### Effect size analysis

To estimate effect sizes, we used each study's standardized regression coefficient (and standard errors) between police force size and crime variables (Higgins and Green 2011; Wilson 2001). Because the impact of police force size on crime is often measured using different methods and metrics across the studies, the direct pooling of regression coefficients is not meaningful (Nieminen et al. 2013). In such a case, standardized regression coefficient may offer a solution. Standardized regression coefficients are the estimates from an analysis carried out on variables that have been standardized to their variances equal to one (Vittinghoff et al. 2005). Therefore, in the context of the police–crime relationship, standardized coefficients show how many standard deviations in the number of crimes will change per a standard deviation increase (or decrease) in the police force size variable. For most of the studies, researchers supplied standardized coefficients, or relevant statistics (e.g., raw coefficient estimate, standard deviations of each variable in the model specification) in tables, figures, or in the body of the text, so we were able to calculate the standardized coefficient estimates of each study.<sup>2</sup> We excluded studies that fail to provide one or more of these components from our systematic review. We then used these standardized coefficients of all 229 findings from 62 studies to estimate the overall effect size in the Stata 14 statistical package.

### Overall effect size

There are two different methods for estimating the overall effect size of police force strength on crime: fixed-effects and random-effects models. Both models rely on the inverse variance weight, so findings with smaller variances (larger studies) contribute more to the weighted average than studies with larger variances (smaller studies) (Helfenstein 2002). However, the final weight in a random-effects model is the inverse

<sup>2</sup> If beta, the standardized regression coefficient, is reported in the estimated regression model, we use beta as the effect size. Standard errors of betas were calculated by applying formula:  $SE(\beta) = \frac{1-r^2}{\sqrt{n-1}}$ , where  $r$  is Pearson or Spearman correlation coefficient. However, if a study reports the raw coefficient estimate ( $= b$ ) as a result of a linear regression, we calculate the standardized coefficient by applying formula:  $\beta = \frac{SD(X)}{SD(Y)}b$ , where  $SD(Y)$  is the standard deviation of the outcome variable while  $SD(X)$  is the standard deviation of the police force size variable used in the study. The standard error for beta is obtained by applying formula:  $SE(\beta) = \frac{SD(X)}{SD(Y)}SE(b)$ . If the standard error was not reported, we obtained it from the confidence interval.

of both study level variance and the estimated between study variance. This gives random-effects models precise type I error rates, so it yields more conservative effect size estimates compared to the fixed-effects model (Lipsey and Wilson 2001). Further, the fixed-effects model assumes that all findings come from the same population, controlled for same variables, use the same outcome definitions, and are otherwise similar to each other with regard to factors that influence analytical findings. This is often an invalid assumption (Higgins et al. 2003; Wilson 2001), and the assumption is unlikely to be valid for the 62 studies and 229 findings we examined. For example, researchers measure police force size using the number of police officers or the dollar amount spent for hiring additional police officers (e.g., GAO 2005). They also frequently rely on a different geographic unit of analysis (e.g., city, county, metropolitan area, state, and nationwide), and analyze different periods. As we have noted, the studies used several different statistical modeling techniques. Due to the presence of heterogeneity across different studies, a random effects model seems to be an appropriate method to estimate the overall effect size.

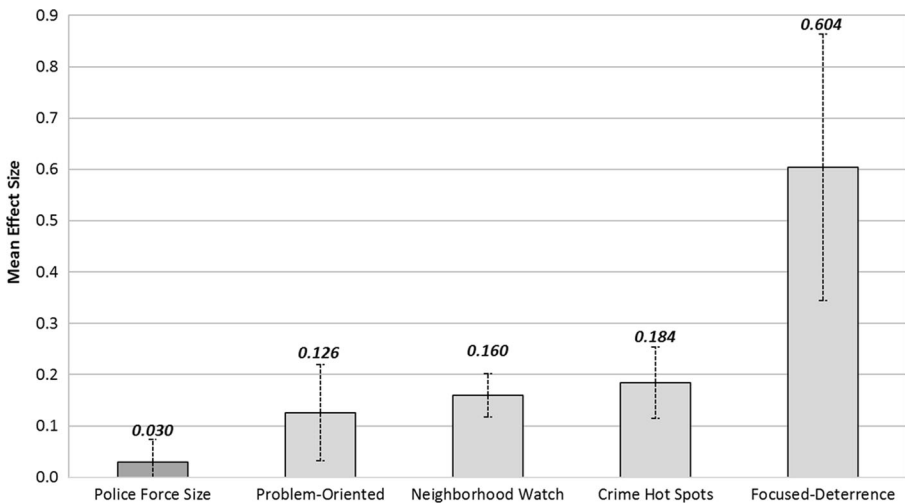
However, a conventional random effects model relies on the assumption that the effect sizes from different studies are independent of one another. This assumption is not valid where multiple findings are nested within the same study. Without considering this dependent nature among multiple findings, a conventional random effects model would incorrectly estimate the overall effect size. To remedy the hierarchical nature of multiple findings per study, we estimated the overall effect size using the robust variance estimation (RVE) technique in meta-analysis (Hedberg 2014; Hedges et al. 2010). The RVE method provides a robust method for estimating standard errors in meta-regression, particularly when there are dependent effects among multiple findings within the same study. However, multiple findings per study can further cluster by the same research group. For example, effect sizes reported in Boba and Lilley (2009) and Lilley and Boba (2008) are likely to cluster at a higher level if the researchers used similar data and statistical method to estimate their effect sizes in several studies. Therefore, it makes sense to assume that the observed effect sizes (findings) are nested within studies, which are further, nested within hierarchically higher-level clusters. So, we used the RVE method with “hierarchical” model weight in Stata to operationalize the hierarchical nature across findings, studies, and research group levels.

We estimated a mean effect size of police force size on crime of about  $-.030$  (with a 95 % confidence interval between  $-.078$  and  $.019$ ).<sup>3</sup> The effect size from the RVE method is not statistically significant. The corresponding tau-squared value ( $= 0.0007$ ; an estimate of the between-clusters variance component) shows that there is a between-clusters variance among the 229 findings nested with 62 studies. The nonsignificant and tiny mean effect size between police force size and crime<sup>4</sup> suggests that simply increasing police force size may not help reduce crime, and if it does, it does not reduce crime by much.

It is instructive to compare this effect size to the effect sizes from other meta-analyses of police strategies, as this provides a set of standards by which to judge the importance of hiring more police. In Fig. 3, we compare this effect size of police force

<sup>3</sup> This is consistent with the results from conventional random-effects model we ran as an exploratory analysis for comparison.

<sup>4</sup> We provide a full list of effect sizes with forest plot for 229 findings in Appendix B.



**Fig. 3** Effect sizes from systematic review studies

size to the effect sizes reported in meta-analyses of crime hot spots (Braga et al. 2014), problem-oriented policing (Weisburd et al. 2010), neighborhood watch (Bennett et al. 2006), and focused-deterrence (Braga and Weisburd 2012). Though all effect sizes for these programs are negatively related to crime, we recalibrate their negative signs into positive (crime prevention gain) signs so that the height of bars corresponds to a bigger impact on crime reduction. It is apparent that the effect size for adding police is miniscule compared to the other effect sizes. Thus, it appears that cities might reduce more crime by using specific strategies to reduce crime than by hiring more police.

One possible explanation for the nonsignificant tiny effect size is that effect size might change over time. If recent studies demonstrate significant effect sizes while older studies report nonsignificant effect sizes, then the nonsignificant effect sizes from older studies might be masking the significant (and more valid) effect sizes of recent studies.

#### *Period effect sizes*

To test whether the effect sizes for police force size and crime have changed over time, we divided our 43-year study period into four overlapping 20-year time periods. This provides sufficient years in each period to show the change in effect sizes over four decades. We assigned the studies (and their findings) to one of the four periods where the dataset of the study was located. For example, Kovandzic and Sloan (2002) analyzed data for the years from 1980 to 1998. The authors found three significant negative relationships and five nonsignificant relationships between police force size and crime. We assigned these findings to 1980–1999 but not to 1990–2013, because the authors' dataset only fit in the first period. This assignment process did force us to drop ten studies and 70 findings from the analysis because these studies overlapped two or more periods.

We calculated the mean effect sizes for each period using the RVE technique. Our findings are shown in Table 3. The effect sizes for four overlapping decades fluctuate from positive, to highly negative, to around zero, to small and negative, but no period

**Table 3** Effect sizes between police force size and crime by decades of dataset

Period	Effect size (random)	<i>p</i> value	Number of findings	Number of studies	Between-clusters differences ( $\tau^2$ )
From 1960 to 1979	.092	.563	59	22	.0281
From 1970 to 1989	-.173	.382	30	17	.1681
From 1980 to 1999	-.003	.646	43	15	.0001
From 1990 to 2013	-.020	.532	71	14	.0026

effect size is significantly different from zero. One persistent finding is clear. The nonsignificant overall effect size is not due to older studies; indeed, the effect size between police strength and crime has been consistently nonsignificant for the past four decades.

However, another possibility for the nonsignificant overall effect size might be due to the methods used. Studies that use weaker methods might be driving the overall nonsignificant effect size. If so, then looking at only strong studies would give a more valid estimate of the average effect size. We look at that next.

## Methods used

Researchers prefer advanced statistical methods because they assume these methods produce more valid findings than more basic correlational techniques. For instance, since Levitt introduced it in 1997, researchers have increasingly employed the instrumental variable (IV) technique to control for the endogenous relationships between police force and crime. Recently, Kovandzic and his colleagues (2016) have suggested that applying generalized method of moments (GMM) provides more advanced specification tests for instruments rather than conventional IV technique. They reanalyzed Levitt's two studies (1997, 2002) and showed that when using GMM they get different results than Levitt. One way of thinking about the history of research on this topic is as an arms race between those supporting and those skeptical of the crime reduction hypothesis, where the arms are statistical methods.

Though newer methods are introduced over time, researchers may not switch to newer methods all at once. We attempt to unravel the context and the history of the use of statistical methods in the study of relationships between police force size and crime. Figure 4 shows that statistical methods change over time. Specifically, prior to 2000, OLS regression was the most used statistical method, but after 2000 other methods became dominant. Studies that use lagged variable models to control the endogenous relationship between police force size and crime also decreased after 2000. Two- and three-stage least squares have not appeared in this literature since 2010.

If the advanced methods consistently produce more valid results, we should see evidence that changes in research methods have changed the size or the sign of effect sizes, regardless of the decade the research was conducted. To test this hypothesis, we used the RVE method with beta as outcome variable, and dummy variables for the methods and measures used. We coded both two-stage least-squared and three-stage-least-squared models as 1 if a study used either statistical model; otherwise 0. We coded

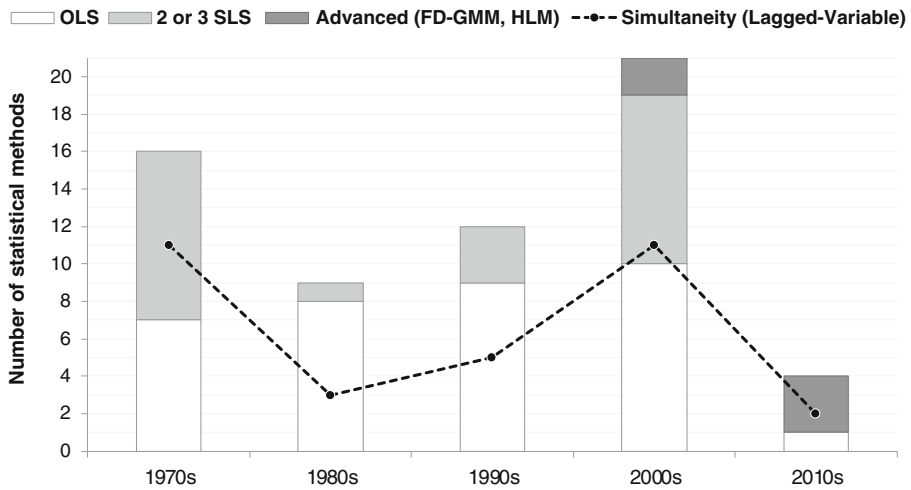


Fig. 4 Statistical methods employed in police force size and crime studies: 1971 through 2013

both generalized method of moments and hierarchical linear model as 1 if a study used either method; otherwise 0. We also considered simultaneity bias between police force size and crime. Levitt (1997) notes that while more police may drive crime down, more crime might prompt elected officials to hire more police. Failing to control for this loop (simultaneity) between the two variables may result in a biased estimate of the relationship between police size and crime. Therefore, we coded the studies that used longitudinal data to control for simultaneity as 1, otherwise 0.

Since choice of statistical method may be linked to other methods choices, we also controlled for the way the independent variable was measured, and the units of analysis used. If a study measures police force size using the amount of dollars spent for hiring additional police officers, we coded the dummy variable as 1. Consequently, any study that measures police force size using the number of police officers or other measures is coded as 0. We also created dummy variables for the geographic unit in which the researchers conducted their study: city or county were coded as 1 and larger units were coded as 0 and used as the reference value.

Table 4 shows no significant relationships between the statistical methods used and effect sizes controlling other factors fixed. This is consistent with the recent findings of Carriaga and Worrall (2015) that neither unit of analysis nor study design has significant impact on the outcome variable. Specifically, using the city or county as unit of analysis does not increase the chances of discovering a crime reduction effect relative to other possible units. We also find that the choice of a geographic unit of analysis does not significantly influence the effect size. Measuring police force size by police budget (rather than by number of officers) does not seem to influence the effect size. These results hint at the possibility that neither statistical method nor measures of police force size and geographic unit of the study have significant impacts on the main relationship between police force and crime. For now, we must conclude that variation in the statistical methods used is not related to effect sizes. While we cannot assert that the next advance in such methods will be unproductive, these results suggest we should not be overly optimistic that newer methods would give us different findings.

**Table 4** Test of advanced method hypothesis in police force size and crime studies

Model variables		Robust variance estimation method with hierarchical model weight schema (DV = effect size)	
		B	<i>p</i> value
(Constant)		.042 (.063)	.516
Categorical variables	City	-.153 (.139)	.295
	County	-.110 (.080)	.253
	2-SLS or 3-SLS	.057 (.156)	.721
	HLM or GMM	-.237 (.110)	.151
	Longitudinal analysis	.041 (.088)	.649
	Police number (by dollar)	-.061 (.071)	.401

Level-1 (Finding level)  $N = 229$ ; Level-2 (study level)  $N = 62$ ;  $\tau^2 = .0093$

### Lack of variation in police force size

Finally, we examine another factor that might explain the tiny and nonsignificant effect size: lack of variation in police force size. In an experiment, the amount of an intervention should exceed a certain dosage, relative to a control, to assure sufficient variation of the intervention variable. If this does not occur, then the independent variable approximates a constant and it will be impossible to measure the impact of the intervention. Something similar to insufficient dosage could influence our estimates of the relationship between police force size and crime study. Specifically, if there is very little change in police force size over time, then whatever impact hiring more cops has on crime may be difficult to detect.

How much change has occurred in police strength over time? To help answer this question we analyzed the temporal change in police force size for different groups of cities based on their populations. The data come from the FBI Table 78, police force size by city agency (Federal Bureau of Investigation [FBI], 2010). The data describe all U.S. cities with population greater than 100,000 between 1990 and 2010 with complete data (about 77 % of all U.S. cities). We divided cities into groups of different populations. In Fig. 5, we display the temporal variation in police per capita of each group over time. Within each group police force size is stable for most of these cities. Only large cities (about 5 % of all cities) with population greater than 1,000,000 show some changes in police force size. There is a growth from 1990 through 1999, and a large decline in 2003. This decline is due to the large decrease in the police force of a single city, New York: the six other cities in the same group did not experience any change in police force size. Table 5 provides further evidence of the stability of police force size over time: standard deviations of the average number of officers are very small relative to their mean values. For the most part, it appears that cities and counties maintain a constant level of police per capita. Large variation in police per capita is not created by hiring and attrition (or firing), but by different size jurisdictions having different levels of policing: bigger jurisdictions have more police per capita than smaller ones.

These findings are very important for four reasons. First, police force size behaves more like a constant than an independent variable, and without much

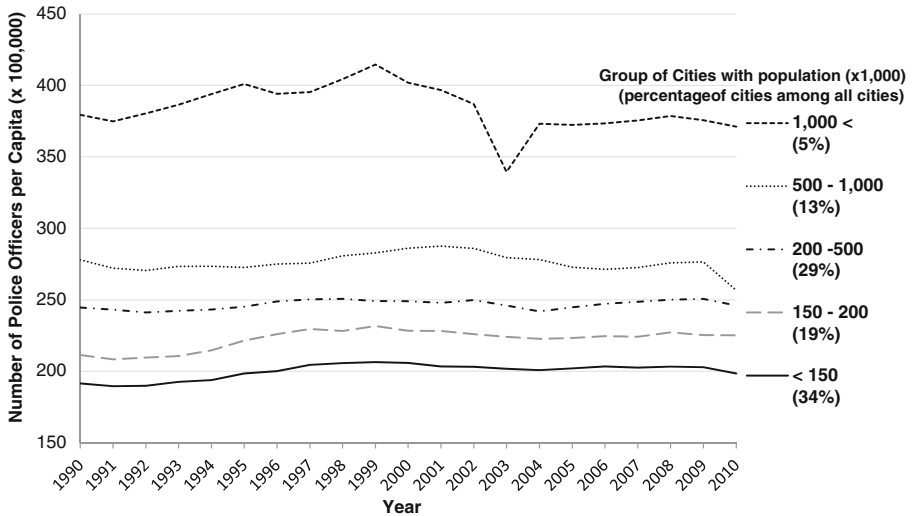


Fig. 5 Police force size rate for U.S. cities grouped by population: 1990 through 2010

variation in an independent variable, it is difficult to find a connection to a dependent variable. Second, the tiny variation in police force size makes any empirical findings about the link to crime highly sensitive to model specification. This would help explain the variation in findings across studies. Third, with high sensitivity, both positive and negative relationships between police force size and crime can be found (as shown in Fig. 2). Finally, the lack of temporal variation also helps explain why studies that made use of temporal changes in police and crime did not produce different findings from those that relied on cross-sectional comparisons only. In conclusion, like the Dude’s rug, this lack of variation brings together the various findings in our systematic review.

### Discussion and conclusions

In review, here are our findings. First, the overall effect size of police force size is negative, small, and statistically not significant. Compared to the effect sizes of

Table 5 Police officers per capita for U.S. cities with populations greater than 100,000: 1990 through 2010

Group of cities with pop (x1000)	Number of cities	Percentage of cities	Mean officers/capita	Standard deviation	Overall change (%)
1000 <	7	4.8 %	384.3	15.8	-2.2
500-1,000	19	13.1 %	276.1	6.6	-7.7
200-500	42	29.0 %	246.7	3.1	0.6
150-200	28	19.3 %	222.4	6.9	6.6
<150	49	33.8 %	200.0	5.2	3.7
Overall	145	100.0 %	291.4	7.0	-1.6

strategies that are (randomized and quasi-experimentally) tested in the policing literature, we conclude that merely increasing police force size does nothing to reduce crime. This finding is different from the most recent meta-analysis of this topic (Carriaga and Worrall 2015).

Second, the reported effect of police force size on crime has been constant and not significant for more than 40 years. This is contrary to what we showed in the descriptive analysis (Fig. 2). There is no good reason to suspect that marginally more police reduce crime at a meaningful level and that more recent research is more supportive of the crime reduction hypothesis.

Third, effect sizes do not appear to be related to the research methods or statistical techniques used in the 62 studies. This conclusion is consistent with Carriaga and Worrall's (2015) analysis of 24 studies.

Fourth, the little temporal variation in police force size from 1990 through 2010 helps explain the tiny and statistically insignificant effect sizes we found. It also might explain why researchers have produced so many contradictory findings over 43 years.

Reconsider Fig. 1. The most optimistic summary of the evidence to date is that police services in the U.S. are located along the right hand end of the curve: any crime control utility from adding more officers will be difficult to detect, particularly given that police agencies are unlikely to make substantial increases in their force sizes. Further, greater progress might be made in police crime-control effectiveness by changing the policing strategy from curve A to curve B. The substantially larger (and statistically significant) effect sizes from meta-analyses of police strategies indicate that policy makers who want police to have an impact on crime would be better suited investing resources in new evidence-based strategies than funding surges in police hiring.

For researchers interested in policing, these findings should be sobering. After more than 40 years of study, during which researchers have used increasingly sophisticated statistical models, we can state that police force size is unlikely to make much difference in crime, on average. However, the increased sophistication of research methods over these four decades has contributed little to improve our understanding of this topic. Unlike Lim and colleagues (2010) and Kovandzic and coauthors (2016), we are not optimistic that further research in this area using statistical modeling is likely to be productive. It is possible that police force size might influence some specific crimes more so than others. Several studies suggest this (e.g., Carriaga and Worrall 2015; GAO 2005; Lim et al. 2010). Unfortunately, we cannot reliably address this question with 62 studies and 229 findings: researchers have not consistently studied the same crime types so we have too few studies to assess this thesis.

Further, the lack of variation in the principle independent variable suggests that any result will be highly sensitive to data and model specification. This is true of crime specific results as well. This explains why findings have appeared to randomly fluctuate over time even when researchers used similar methods and datasets to decipher the relationship between police force size and crime.

We should put the weak, and possibly nonexistent, connection between police force size and crime in context. This finding is part of a larger literature that indicates that the types of methods used to answer this type of question may not be up to the task. After reviewing the research on the impact of the death penalty and crime Daniel Nagin (2013, p. 92), for example, concludes that "This unpredictability calls into question the



usefulness of prior data on the death penalty when calculating present and future risk.” Looking outside of the criminal justice policy literature, we find a similar conclusion in education policy research. In the conclusions of an article on the effects of classroom size on future earnings of students, Dustmann et al. (2003: F118-19) state, “The main result of our analysis is that class size effects on wages are present, but very small. They are unlikely to be detected in simple reduced form regressions when using data sets of moderate size.” Hanushek (2002) comes to the same conclusion.

Within this context, our results seem unremarkable. However, because of this context the major implication of our systematic review is clear: researchers should reconsider efforts to link simple police outcomes to simple inputs using nonexperimental statistical modeling. In contrast to the quasi- and randomized controlled experimental literature, nonexperimental studies are easy to implement, but their collective findings maybe too weak and unreliable to inform policy. Here we break with the traditional way of concluding a research paper. We anticipate little benefit to pursuing this line of enquiry, and suggest that it is time to end it.

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## References

### \* Denotes a study included in both the systematic review and meta-analysis

- Andenaes, J. (1974). *Punishment and deterrence*. Ann Arbor: University of Michigan Press.
- \*Bahl, R. W., Gustely, R. D., & Wasylenko, M. J. (1978). The determinants of local government police expenditures: a public employment approach. *National Tax Journal*, 31(1), 67–79.
- \*Baltagi, B. H. (2006). Estimating an economic model of crime using panel data from North Carolina. *Journal of Applied Econometrics*, 21(4), 543–547.
- Becker, G. S. (1968). Crime and punishment: an economic approach. *The Journal of Political Economy*, 76(2), 169–217.
- Bennett, T., Holloway, K., & Farrington, D. P. (2006). Does neighborhood watch reduce crime? A systematic review and meta-analysis. *Journal of Experimental Criminology*, 2(4), 437–458.
- \*Benson, B. L., Rasmussen, D. W., & Kim, I. (1998). Deterrence and public policy: trade-offs in the allocation of police resources. *International Review of Law and Economics*, 18(1), 77–100.
- \*Boba, R., & Lilley, D. (2009). Violence Against Women Act (VAWA) funding a nationwide assessment of effects on rape and assault. *Violence Against Women*, 15(2), 168–185.
- Braga, A. A., & Weisburd, D. L. (2012). The effects of focused deterrence strategies on crime: a systematic review and meta-analysis of the empirical evidence. *Journal of Research in Crime and Delinquency*, 49(3), 323–358.
- Braga, A. A., Papachristos, A. V., & Hureau, D. M. (2014). The effects of hot spots policing on crime: an updated systematic review and meta-analysis. *Justice Quarterly*, 31(4), 633–663.
- \*Britt, D. W., & Tittle, C. R. (1975). Crime rates and police behavior: a test of two hypotheses. *Social Forces*, 54(2), 441–451.
- \*Brown, M. A. (1982). Modelling the spatial distribution of suburban crime. *Economic Geography*, 58(3), 247–261.

- \*Buonanno, P., & Mastrobuoni, G. (2012). Police and crime: Evidence from dictated delays in centralized police hiring (IZA Discussion Paper No. 6477). Retrieved from Social Science Research Network: <http://ssrn.com/abstract=2039663>.
- Carriaga, M. L., & Worrall, J. L. (2015). Police levels and crime: a systematic review and meta-analysis. *The Police Journal*, 88(4), 315–333.
- \*Chalfin, A., & McCrary, J. (2013). *The effect of police on crime: New evidence from US cities, 1960–2010* (Working Paper No. 18815). Retrieved from National Bureau of Economic Research website: <http://www.nber.org/papers/w18815>.
- \*Chamlin, M. B., & Langworthy, R. H. (1996). The police, crime, and economic theory: a replication and extension. *American Journal of Criminal Justice*, 20(2), 165–182.
- \*Cloninger, D. O. (1975). The deterrence effect of law enforcement: an evaluation of recent findings and some new evidence. *American Journal of Economics and Sociology*, 34(3), 323–335.
- \*Cloninger, D. O., & Sartorius, L. C. (1979). Crime rates, clearance rates and enforcement effort: the case of Houston, Texas. *American Journal of Economics and Sociology*, 38(4), 389–402.
- Cook, D. J., Mulrow, C. D., & Haynes, R. B. (1997). Systematic reviews: synthesis of best evidence for clinical decisions. *Annals of Internal Medicine*, 126(5), 376–380.
- \*Corman, H., & Joyce, T. (1990). Urban crime control: violent crimes in New York City. *Social Science Quarterly*, 71(3), 567–584.
- \*Corman, H., & Mocan, H. N. (2000). A time-series analysis of crime, deterrence, and drug abuse in New York City. *American Economic Review*, 90(3), 584–604.
- \*Corman, H., & Mocan, N. (2005). Carrots, sticks, and broken windows. *Journal of Law and Economics*, 48(1), 235–266.
- \*Corman, H., Joyce, T., & Lovitch, N. (1987). Crime, deterrence and the business cycle in New York City: a VAR Approach. *The Review of Economics and Statistics*, 69(4), 695–700.
- \*Cornwell, C., & Trumbull, W. N. (1994). Estimating the economic model of crime with panel data. *The Review of Economics and Statistics*, 76(2), 360–366.
- \*Deutsch, J., Hakim, S., & Spiegel, U. (1990). The effects of criminal experience on the incidence of crime. *American Journal of Economics and Sociology*, 49(1), 1–5.
- Dustmann, C., Rajah, N., & Soest, A. (2003). Class size, education, and wages. *The Economic Journal*, 113(485), 99–120.
- \*Ehrlich, I. (1973). Participation in Illegitimate Activities: a theoretical and empirical investigation. *Journal of Political Economy*, 81(3), 521–565.
- \*Evans, W. N., & Owens, E. G. (2007). COPS and crime. *Journal of Public Economics*, 91(1), 181–201.
- \*Friedman, J., Hakim, S., & Spiegel, U. (1989). The difference between short and long run effects of police outlays on crime: policing deters criminals initially, but later they may “Learn by Doing”. *American Journal of Economics and Sociology*, 48(2), 177–191.
- \*Fujii, E. T., & Mak, J. (1979). The impact of alternative regional development strategies on crime rates: tourism vs. agriculture in Hawaii. *The Annals of Regional Science*, 13(3), 42–56.
- \*Gould, E. D., Weinberg, B. A., & Mustard, D. B. (2002). Crime rates and local labor market opportunities in the United States: 1979–1997. *Review of Economics and Statistics*, 84(1), 45–61.
- \*Government Accountability Office (2005). *Community policing grants: COPS grants were a modest contributor to declines in crime in the 1990s*. (GAO Publication No. GAO-06-104). Washington, DC: U.S. Government Printing Office.
- \*Greenberg, D. F., Kessler, R. C., & Loftin, C. (1983). The effect of police employment on crime. *Criminology*, 21(3), 375–394.
- \*Greenwood, M. J., & Wadycki, W. J. (1973). Crime rates and public expenditures for police protection: their interaction. *Review of Social Economy*, 31(2), 138–151.
- \*Hakim, S. (1980). The attraction of property crimes to suburban localities: a revised economic model. *Urban Studies*, 17(3), 265–276.
- \*Hakim, S., Ovadia, A., & Weinblatt, J. (1978). Crime attraction and deterrence in small communities: theory and results. *International Regional Science Review*, 3(2), 153–163.
- \*Hakim, S., Ovadia, A., Sagi, E., & Weinblatt, J. (1979). Interjurisdictional spillover of crime and police expenditure. *Land Economics*, 54(2), 200–212.
- Hanushek, E. A. (2002). Evidence, politics, and the class size debate. In L. Mishel, R. Rothstein, A. B. Krueger, E. A. Hanushek, & J. K. Rice (Eds.), *The class size debate* (pp. 37–65). Washington, DC: Economic Policy Institute.
- \*Harcourt, B. E., & Ludwig, J. (2006). Broken windows: new evidence from New York City and a five-city social experiment. *University of Chicago Law Review*, 73(1), 271–320.

- Hedberg, E. C. (2014). *ROBUMETA: Stata module to perform robust variance estimation in meta-regression with dependent effect size estimates. Statistical Software Components*. Retrieved from <https://ideas.repec.org/c/boc/bocode/s457219.html>.
- Hedges, L. V., Tipton, E., & Johnson, M. C. (2010). Robust variance estimation in meta-regression with dependent effect size estimates. *Research Synthesis Methods, 1*(1), 39–65.
- Helfenstein, U. (2002). Data and models determine treatment proposals—an illustration from meta-analysis. *Postgraduate Medical Journal, 78*(917), 131–134.
- Higgins, J. P., & Green, S. (2011). *Cochrane handbook for systematic reviews of interventions: Version 5.1.0 (updated March 2011)*. The Cochrane collaboration. Retrieved from [www.cochrane-handbook.org](http://www.cochrane-handbook.org).
- Higgins, J. P., Thompson, S. G., Deeks, J. J., & Altman, D. G. (2003). Measuring inconsistency in meta-analyses. *British Medical Journal, 327*(7414), 557–560.
- \*Howsen, R. M., & Jarrell, S. B. (1987). Some determinants of property crime: economic factors influence criminal behavior but cannot completely explain the syndrome. *American Journal of Economics and Sociology, 46*(4), 445–457.
- \*Humphries, D., & Wallace, D. (1980). Capitalist accumulation and urban crime. *Social Problems, 28*(2), 179–193.
- \*Kim, M. (2007). *Reassessing the effects of police manpower changes on crime rates: Evidence from a dynamic panel model* (Unpublished doctoral dissertation). University at Albany, State University of New York.
- \*Kleck, G., & Barnes, J. C. (2014). Do more police lead to more crime deterrence? *Crime & Delinquency, 60*(5), 716–738.
- \*Klick, J., & Tabarrok, A. (2005). Using terror alert levels to estimate the effect of police on crime. *Journal of Law and Economics, 48*(1), 267–279.
- \*Kovandzic, T. V., & Sloan, J. J. (2002). Police levels and crime rates revisited: a county-level analysis from Florida (1980–1998). *Journal of Criminal Justice, 30*(1), 65–76.
- Kovandzic, T. V., Schaffer, M. E., Vieraitis, L. M., Orrick, E. A., & Piquero, A. R. (2016). Police, crime and the problem of weak instruments: revisiting the “more police, less crime” thesis. *Journal of Quantitative Criminology, 32*(1), 133–158.
- \*Land, K. C., & Felson, M. (1976). A general framework for building dynamic macro social indicator models: including an analysis of changes in crime rates and police expenditures. *American Journal of Sociology, 82*(3), 565–604.
- \*Levitt, S. D. (1997). Using electoral cycles in police hiring to estimate the effect of police on crime. *American Economic Review, 87*(3), 270–90.
- \*Levitt, S. D. (2002). Using electoral cycles in police hiring to estimate the effect of police on crime: reply. *American Economic Review, 92*(4), 1244–1250.
- \*Lilley, D., & Boba, R. (2008). A comparison of outcomes associated with two key law-enforcement grant programs. *Criminal Justice Policy Review, 19*(4), 438–465.
- \*Lilley, D., & Boba, R. (2009). Crime reduction outcomes associated with the State Criminal Alien Assistance Program. *Journal of Criminal Justice, 37*(3), 217–224.
- Lipsey, M. W., & Wilson, D. B. (2001). *Practical meta-analysis*. Thousand Oaks: Sage Publications.
- Lim, H., Lee, H., & Cuvelier, S. J. (2010). The impact of police levels on crime rates: a systematic analysis of methods and statistics in existing studies. *Pacific Journal of Police & Criminal Justice, 8*(1), 49–82.
- \*Lin, M. J. (2009). More police, less crime: evidence from US state data. *International Review of Law and Economics, 29*(2), 73–80.
- \*Liu, Y., & Bee, R. H. (1983). Modeling criminal activity in an area in economic decline: local economic conditions are a major factor in local property crimes. *American Journal of Economics and Sociology, 42*(4), 385–392.
- \*MacDonald, J. M. (2002). The effectiveness of community policing in reducing urban violence. *Crime & Delinquency, 48*(4), 592–618.
- Makinen, T., & Takala, H. (1980). The 1976 police strike in Finland. *Scandinavian Studies in Criminology, 7*(1), 87–106.
- \*Marvell, T. B., & Moody, C. E. (1996). Specification problems, police levels, and crime rates. *Criminology, 34*(4), 609–646.
- Mazerolle, L., & Ransley, J. (2006). *Third party policing*. Cambridge: Cambridge University Press.
- \*McCrary, J. (2002). Using electoral cycles in police hiring to estimate the effect of police on crime: comment. *American Economic Review, 92*(4), 1236–1243.
- \*McPheters, L. R., & Stronge, W. B. (1974). Law enforcement expenditures and urban crime. *National Tax Journal, 27*(4), 633–644.

- \*Mehay, S. L. (1977). Interjurisdictional spillovers of urban police services. *Southern Economic Journal*, 43(3), 1352–1359.
- \*Mikesell, J., & Pirog–Good, M. A. (1990). State lotteries and crime. *American Journal of Economics and Sociology*, 49(1), 7–20.
- \*Morris, D., & Tweeten, L. (1971). The cost of controlling crime: a study in economies of city life. *The annals of regional science*, 5(1), 33–49.
- \*Muhlhausen, D. (2001). *Do community oriented policing services grants affect violent crime rates. A report of the heritage center for data analysis*. Washington, DC: The Heritage Foundation.
- Mulrow, C. D., & Oxman, A. (1997). *How to conduct a Cochrane systematic review: Version 3.0.2*. San Antonio: The Cochrane Collaboration.
- Nagin, D. S. (2013). Deterrence: a review of the evidence by a criminologist for economists. *Annual Review of Economics*, 5(1), 83–105.
- Nagin, D. S., Solow, R. M., & Lum, C. (2015). Deterrence, criminal opportunities, and police. *Criminology*, 53(1), 74–100.
- Nieminen, P., Lehtiniemi, H., Vähäkangas, K., Huusko, A., & Rautio, A. (2013). Standardised regression coefficient as an effect size index in summarising findings in epidemiological studies. *Epidemiology, Biostatistics and Public Health*, 10(4), 1–15.
- \*Niskanen, W. A. (1994). *Crime, police, and root causes. Policy Analysis 218*. Washington, DC: Cato Institute.
- \*Pogue, T. F. (1975). Effect of police expenditures on crime rates: some evidence. *Public Finance Review*, 3(1), 14–44.
- \*Ren, L., Zhao, J., & Lovrich, N. P. (2008). Liberal versus conservative public policies on crime: what was the comparative track record during the 1990s? *Journal of Criminal Justice*, 36(4), 316–325.
- Russell, F. (1930, reprinted 1975). *A City in Terror: Calvin Coolidge and the 1919 Boston Police Strike*. Boston: Beacon Press.
- \*Sollars, D. L., Benson, B. L., & Rasmussen, D. W. (1994). Drug enforcement and the deterrence of property crime among local jurisdictions. *Public Finance Review*, 22(1), 22–45.
- \*Swimmer, E. (1974). Measurement of the effectiveness of urban law enforcement: a simultaneous approach. *Southern Economic Journal*, 40(4), 618–630.
- \*Swimmer, G. (1974). The relationship of police and crime. *Criminology*, 12(3), 293–314.
- \*Tauchen, H., Witte, A. D., & Griesinger, H. (1994). Criminal deterrence: revisiting the issue with a birth cohort. *The Review of Economics and Statistics*, 76(3), 399–412.
- U.S. Department of Justice, Federal Bureau of Investigation (2010). Full-time law enforcement employees by state by city: Selected years, 1990 through 2010. In *Crime in the United States 2010*. Retrieved from <https://www.fbi.gov/about-us/cjis/ucr/crime-in-the-u.s/2010/crime-in-the-u.s.-2010/police-employee-data/tables/10tbl78.xls/view>.
- \*Van Tulder, F. (1992). Crime, detection rate, and the police: a macro approach. *Journal of Quantitative Criminology*, 8(1), 113–131.
- Vittinghoff, E., Glidden, D. V., Shiboski, S. C., & McCulloch, C. E. (2005). *Regression methods in biostatistics: Linear, logistic, survival, and repeated measures models*. New York: Springer.
- Weisburd, D., Telep, C. W., Hinkle, J. C., & Eck, J. E. (2010). Is problem-oriented policing effective in reducing crime and disorder? *Criminology & Public Policy*, 9(1), 139–172.
- Wilson, D. B. (2001). Meta-analytic methods for criminology. *The Annals of the American Academy of Political and Social Science*, 578(1), 71–89.
- \*Worrall, J. L., & Kovandzic, T. V. (2007). COPS grant and crime. *Criminology*, 45(1), 159–190.
- \*Worrall, J. L., & Kovandzic, T. V. (2010). Police levels and crime rates: an instrumental variables approach. *Social Science Research*, 39(3), 506–516.
- \*Zedlewski, E. W. (1983). Deterrence findings and data sources: a comparison of the Uniform Crime Reports and the National Crime Surveys. *Journal of Research in Crime and Delinquency*, 20(2), 262–276.
- \*Zhao, J. S., Scheider, M. C., & Thurman, Q. (2002). Funding community policing to reduce crime: have COPS grants made a difference? *Criminology & Public Policy*, 2(1), 7–32.

**YongJei Lee** is a PhD candidate in the School of Criminal Justice, University of Cincinnati. He received a master's degree in public policy and management from Carnegie Mellon University. His current research examines police effectiveness, crime hot spots detection and forecasting algorithm, and the concentration of crime at places, offenders, and victims. For this paper, his role was to gather the studies using a systematic review process, conduct the statistical analysis, and write the paper.

**John E. Eck** specializes in police effectiveness and crime prevention. He has been active in research in these areas since 1977, and with the University of Cincinnati since 1998. Eck has studied investigations effectiveness and problem-oriented policing. Since the mid-1990s he has focused much of his attention to examining why crime and disorder is highly concentrated at specific addresses and what police and others can do about this. Having monitored research findings on police force size and crime for his entire professional career, he became curious as to whether decades of study had resulted in anything useful. In this paper, his principle contribution was to launch the investigation, supervise the research, and edit drafts.

**Nicholas Corsaro** is an Associate Professor at the School of Criminal Justice at the University of Cincinnati. His research focuses on the role of the police in crime prevention with a particular emphasis on the use of strategies, tactics, and organizational policies. For this paper, he provided assistance in structuring the statistical analysis, interpreting the findings, and provided editorial feedback.