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REPLICATION

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Narrow and wide replication of Chalfin and McCrary (REStat, 2018)

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Summary

We undertake a narrow and wide replication of "Are US Cities Underpoliced? Theory and Evidence" by Chalfin and McCrary. Using data from medium to large cities in the United States from 1960 to 2010, the authors estimate the effect of police on crime. To correct for the presence of measurement error, they propose to combine the information from two proxies of the police variable within the generalized method of moments framework. Throughout our replication exercise, we find that, in general, the original results are robust to computation in R compared to STATA and to the inclusion of more recent data (until 2019).

KEYWORDS

crime, GMM, IV, replication, R, STATA

1 | INTRODUCTION

Chalfin and McCrary (2018) estimate the police elasticity of crime using data from 242 medium and large cities in the United States, over the period 1960-2010. The question of the effect of police on crime has been studied extensively, and it has been established that the data on measuring police employment suffers from measurement errors, casting doubt on the magnitude as well as the precision of estimates (Eck & Maguire, 2005; Levitt, 1998a, 1998b; Mosher et al., 2011). In the context of the theories of deterrence (Becker, 1968; Bentham, 1948) police is often viewed as a crucial element for crime prevention. However, the estimates for police elasticity in the empirical literature are often found to be very small and with counterintuitive sign. These results are typically attributed to simultaneity bias.

Chalfin and McCrary's contribution is methodological as well as empirical. They argue that a further source of bias is due to mismeasurement of the police variable. Under the classical measurement error assumption, the coefficient of the mismeasured variable will be estimated with an attenuation bias that would explain the small magnitude of the estimates found in the literature.[1] Chalfin and McCrary also stress that, from a welfare perspective, violent crimes are comparatively more costly than property crimes. This puts more emphasis on the ability of police of reducing the former type of crime, particularly murder, rather than crime in general.

First, they tackle the issue of measurement error in police employment by combining data from two sources: the Uniform Crime Report (UCR) from the FBI and the Annual Survey of Government (ASG) extracted from the US Census. Assuming a classical measurement error structure, the authors use the result that two proxies of the same unobserved variable, when instrumented upon each other, produce a consistent estimator. The corresponding instrumental variable (IV) moment conditions are then stacked together, and the parameters of interest are estimated via the generalized method of moments (GMM). Furthermore, by stacking the moment conditions corresponding to two different crimes, we can test for equality of police elasticity for the two crimes: for example, when we compare property crimes and violent crimes. Over-

[1]As noted in Chalfin and McCrary (2018), adding covariates to mitigate further confounding bias may strengthen the effect of the attenuation bias.

all, their results match the intuition provided by deterrence theories: once measurement errors are taken into account, elasticities are negative and tend to be larger for violent crimes than for property crimes. If simultaneity is present, the estimates are likely to be conservative. Such results suggest that an increase in police in the cities considered in the study would have increased social welfare.

In this paper, we first undertake a narrow replication of Chalfin and McCrary's key results, where we estimate the police elasticities of violent and property crimes, both aggregated and disaggregated, using ordinary least squares (OLS), IV, and GMM estimators. We then extend the dataset up to 2019 and undertake a wide replication as a test for robustness. In our replication exercise, to complement the authors' results, we introduce a further estimation method, due to Andersson and Møen (2016), that optimally combines two consistent IV estimators for the classical errors-in-variables problem. We refer to this estimator as OptIV. The rest of the paper is organized as follows: Section 2 outlines the econometric model, while Section 3 gives details about the data used. Section 4 presents summary statistics, narrow and wide replication. Section 5 concludes and briefly discusses the implications of the replicated results. Additional results can be found in the supporting information Appendix.

2 | ECONOMETRIC MODEL

Chalfin and McCrary (2018) consider the following model

$$Y_i = \theta S_i^* + X_i'\gamma + e_i, \quad i = 1, \dots, N \tag{1}$$

where N is the number of cities, Y_i is the year-on-year log change in any given crime for a given city i, S_i^* is the true yet unobservable variable for police, and X_i is the vector of covariates.[2] The UCR and ASG variables, denoted as S_i and Z_i respectively, measure the year-on-year log change in observed police and are related to S_i^* via a classical measurement error relationship. This is

$$S_i = S_i^* + u_i \tag{2}$$

$$Z_i = S_i^* + v_i \tag{3}$$

where the measurement errors u_i and v_i are mutually uncorrelated and uncorrelated with the disturbance term e_i in Equation (1). The parameter of interest θ is interpreted as the police elasticity of crime.

It is well-known (see, e.g., Verbeek, 2017, chapter 5) that if we replace the latent variable S_i^* with an observed proxy (either S_i or Z_i), the OLS estimator is biased and inconsistent. Chalfin and McCrary suggest estimating the parameters in Equation (1) by replacing S_i^* with, say, S_i and use Z_i as an instrument. The resulting two-stage least squares (2SLS) estimator is referred to as the *forward* IV estimator. By switching the role of the two proxies, we obtain another consistent 2SLS estimator, namely, the *reflected* IV estimator (Ashenfelter & Krueger, 1994). We can stack the moment conditions of the two IV estimators as shown in Equation (4):

$$\mathbf{g}_i(\boldsymbol{\beta}) = W_i \begin{pmatrix} Z_i(Y_i - \theta_1 S_i - X_i'\gamma_1) \\ X_i(Y_i - \theta_1 S_i - X_i'\gamma_1) \\ S_i(Y_i - \theta_2 Z_i - X_i'\gamma_2) \\ X_i(Y_i - \theta_2 Z_i - X_i'\gamma_2) \end{pmatrix} \tag{4}$$

where W_i refers to the 2010 city population and $\boldsymbol{\beta}$ is an implicitly defined vector of parameters. The parameter vector $\boldsymbol{\beta}$ can be estimated via GMM. Furthermore, by imposing $\theta_1 = \theta_2 = \theta$, we get an overidentified system of equations. The OptIV estimator for θ, on the other hand, is defined as

$$\hat{\theta}_\lambda = \lambda\hat{\theta}_f + (1-\lambda)\hat{\theta}_r \tag{5}$$

with $\hat{\theta}_f$ and $\hat{\theta}_r$ denoting the forward and reflected IV estimators, respectively. The optimal value of λ (i.e., the value that guarantees the smallest variance for $\hat{\theta}_\lambda$) is

$$\lambda_{opt} = \frac{v_r - c_{fr}}{v_f + v_r - 2c_{fr}}$$

[2]In the empirical exercise, the covariates X_i are filtered away via the Frisch–Waugh–Lovell theorem.

where v_f and v_r are the variances of the forward and reflected IV estimators, respectively, while c_{fr} is their covariance. To compute standard errors, we use

$$Var[\hat{\theta}_\lambda] = \lambda^2 v_f + (1-\lambda)^2 v_r + 2(1-\lambda)c_{fr}.$$

This approach is made operational by replacing v_f, v_r, and c_{fr} with suitable estimators (see Andersson & Møen, 2016, for further details).

3 | DATA

The original sample used by Chalfin and McCrary consists of 10,589 observations consisting of 242 cities with population over 50,000, across the period 1960–2010. Our dataset extends the same sample till 2019, increasing the sample size to 12,023. This section describes the key variables, as well as the sources used in the original and extended dataset.

The key variables used for the estimation of the police elasticity are crimes and full-time police employment. Chalfin and McCrary measure the elasticity for nine types of crimes, namely, murder, rape, robbery, assault, burglary, larceny, motor vehicle theft, all violent crimes, and all property crimes. This classification follows the Return A records maintained by the FBI.[3,4] To estimate the benefit of spending the marginal dollar on police, Chalfin and McCrary also estimate the cost-weighted elasticity of all crimes, with the costs of each crime taken from the literature. The data for each crime are taken from the FBI's UCR, published every year.

The UCR measure of police employment is taken from the Law Enforcement Officers Killed and Assaulted (LEOKA) database maintained by the FBI. The measure considered here includes only full-time sworn officers. The ASG measure is taken from the Annual Survey of Public Employment and Payroll (ASPEP) published by the US Census Bureau. Chalfin and McCrary include the ASG and UCR measures of city population in the regressions as controls, with both measures coming from the databases mentioned above.

For the narrow replication, we obtain the data from the replication files provided by the authors.[5] For the wide replication, the extended dataset (from 2011 onwards) for crime was obtained from Dr. Jacob Kaplan's database.[6] The data for the UCR measure of police employment as well as city population were also taken from the same website. For the ASG measure of police as well as city population from 2011 onwards, we extracted the data from the ASPEP tables published on the US Census website. The final dataset used for the wide replication consists of the authors' files from 1962 to 2010 and the data obtained from the sources mentioned above from 2011 to 2019. For replication results with the “novel” dataset, that is, the dataset with all variables computed from Dr. Kaplan's files over the period 1962–2019, see supporting information Appendix.

4 | RESULTS

4.1 | Summary statistics

We begin by discussing the relevant summary statistics for both the original as well as the extended dataset. Table 1 shows the mean, standard deviation as well as the minimum and maximum values of the growth rates of all the Return A crimes used in the paper, cost-weighted sum of all crimes as well the UCR and ASG measure of full-time sworn police employment.

The growth rates for most of the Return A crimes remain largely unchanged, with one exception: the mean growth rate of burglaries have gone from from 1.4% to almost zero. Growth rates of violent and property crimes have marginally fallen as well. Overall, the extended sample is fairly similar to the original sample at the mean. With this in mind, we now move on to the results of the narrow and wide replications.

[3] The Return A Master File furnishes the number of Part I Offences (murder and nonnegligent manslaughter, rape, robbery, aggravated assault, burglary, larceny theft, motor vehicle theft,and arson), the reported number of police officers killed and assaulted, and clearances involving juveniles.

[4] https://ucr.fbi.gov/additional-ucr-publications/ucr_handbook.pdf

[5] https://eml.berkeley.edu/~jmccrary/

[6] https://www.openicpsr.org/openicpsr/project/100707/version/V17/view

TABLE 1 Summary statistics for the original and extended dataset.

	Crime	N	Mean	St. dev.	Min	Max
Original dataset	Murder	10,589	0.014	0.570	−2.792	2.446
	Rape	10,589	0.043	0.426	−4.384	4.199
	Robbery	10,589	0.039	0.255	−1.792	1.946
	Aggravated assault	10,589	0.044	0.298	−2.833	3.129
	Burglary	10,589	0.014	0.176	−1.549	1.410
	Larceny	10,589	0.016	0.146	−1.435	2.146
	Motor vehicle theft	10,589	0.014	0.200	−1.516	1.447
	Sum of violent crimes	10,589	0.040	0.209	−1.804	1.467
	Sum of property crimes	10,589	0.016	0.131	−1.304	1.248
	Cost-weighted sum of all crimes	10,589	0.022	0.411	−2.363	3.033
	Sworn police, UCR	10,589	0.013	0.062	−1.359	1.148
	Sworn police, ASG	10,589	0.013	0.091	−1.402	1.288
Extended dataset	Murder	12,023	0.014	0.569	−2.792	2.457
	Rape	12,023	0.045	0.417	−4.384	4.199
	Robbery	12,023	0.029	0.252	−1.792	1.946
	Aggravated assault	12,023	0.038	0.289	−2.833	3.129
	Burglary	12,023	0.001	0.182	−1.549	1.410
	Larceny	12,023	0.012	0.148	−1.498	2.146
	Motor vehicle theft	12,023	0.012	0.209	−4.007	2.197
	Sum of violent crimes	12,023	0.035	0.206	−1.804	1.537
	Sum of property crimes	12,023	0.009	0.135	−1.455	1.598
	Cost-weighted sum of all crimes	12,023	0.020	0.394	−2.363	3.033
	Sworn police, UCR	12,023	0.012	0.062	−1.359	1.148
	Sworn police, ASG	12,023	0.012	0.090	−1.402	1.288

Abbreviations: ASG, Annual Survey of Government; UCR, Uniform Crime Report.

4.2 | Narrow replication

Table 2 presents the results of the narrow replication of the Chalfin and McCrary's paper. Specifically, it shows regression results of all the growth rates of Return A crimes, as well as the sum of cost-weighted violent, property and all crimes on the first lag of growth rates of the UCR measure of police employment (Columns 1 and 2) and the ASG measure of police employment (Columns 3 and 4), respectively. Columns 1 and 3 have only year fixed effects, while Columns 2 and 4 have state-year fixed effects included.

Columns 5 to 8 show the results of the forward and reflected IV estimators, while Column 9 reports the GMM estimates. The authors argue that elasticities reported in Column 9 are their best estimate of the effect of a percentage increase in police on each of the crimes. Column 10 reports the results for the OptIV estimator: In this case, the magnitudes and signs of the estimated parameters are comparable with those obtained via GMM; the standard errors are also very similar.

The replicated results exactly match Chalfin and McCrary's results. The size of the OLS coefficients is much smaller than the IV and GMM estimated results, confirming that both the UCR and ASG data are likely contaminated by measurement error. Particularly, the magnitudes for both the reflected and forward IV estimates are much larger than their OLS counterparts. The largest elasticities are for murder, motor vehicle theft, and robbery (Columns 5–8). The elasticities for these crimes continue to be the largest both in the GMM and OptIV estimates as well. Furthermore, the elasticity of all violent crimes is double that of property crimes. We estimated our results to R (compared with STATA), indicating that Chalfin and McCrary's estimates are robust to change in software.

The results in Table 3 report the *p*-values for a two tail *t*-test of equality of coefficients, as seen in Table 6 of Chalfin and McCrary (2018). Differently from what we find in Table 2, the results are not an exact match. In most cases, however, the interpretation remains the same. If we consider the conventional 5% level of significance, the test for the pair murder-burglary produces a *p*-value of 0.035 versus the 0.058 *p*-value found in Chalfin and McCrary, while for the comparison between the sum of property crimes and the sum of violent crimes, we find a *p*-value of 0.046 against the 0.075 *p*-value of the original paper.

TABLE 2 Estimates of effect of police on crime (original dataset).

	OLS				2SLS				Pooled models	
	UCR measure		ASG measure		UCR measure (forward)		ASG measure (reflected)		GMM	OptIV
Crime	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Murder	−0.270	−0.204	−0.148	−0.143	−0.804	−0.889	−0.743	−0.572	−0.666	−0.663
	(0.071)	(0.097)	(0.047)	(0.059)	(0.260)	(0.330)	(0.197)	(0.243)	(0.218)	(0.218)
Rape	−0.066	−0.074	−0.038	−0.054	−0.206	−0.339	−0.187	−0.208	−0.255	−0.255
	(0.069)	(0.092)	(0.043)	(0.050)	(0.233)	(0.279)	(0.187)	(0.231)	(0.202)	(0.202)
Robbery	−0.180	−0.204	−0.085	−0.084	−0.458	−0.521	−0.496	−0.572	−0.559	−0.559
	(0.048)	(0.047)	(0.032)	(0.029)	(0.176)	(0.161)	(0.127)	(0.118)	(0.108)	(0.108)
Aggravated assault	−0.052	−0.037	−0.010	−0.013	−0.050	−0.079	−0.148	−0.104	−0.099	−0.099
	(0.043)	(0.050)	(0.030)	(0.035)	(0.164)	(0.193)	(0.120)	(0.126)	(0.117)	(0.117)
Burglary	−0.061	−0.062	−0.041	−0.054	−0.221	−0.339	−0.169	−0.174	−0.225	−0.224
	(0.043)	(0.037)	(0.027)	(0.021)	(0.144)	(0.118)	(0.118)	0.094	(0.082)	(0.082)
Larceny	−0.038	−0.025	−0.002	−0.018	−0.012	−0.113	−0.104	−0.070	−0.083	−0.083
	(0.031)	(0.027)	(0.021)	(0.017)	(0.115)	(0.095)	(0.084)	(0.069)	(0.062)	(0.062)
Motor vehicle theft	−0.187	−0.131	−0.109	−0.047	−0.592	−0.292	−0.515	−0.367	−0.343	−0.343
	(0.049)	(0.043)	(0.031)	(0.025)	(0.168)	(0.138)	(0.130)	(0.109)	(0.093)	(0.093)
Violent crimes	−0.117	−0.120	−0.053	−0.058	−0.288	−0.361	−0.324	−0.336	−0.344	−0.344
	(0.037)	(0.040)	(0.024)	(0.023)	(0.127)	0.131	(0.100)	(0.100)	(0.088)	(0.088)
Property crimes	−0.071	−0.006	−0.028	−0.030	−0.151	−0.189	−0.197	−0.167	−0.174	−0.173
	(0.028)	(0.026)	(0.020)	(0.015)	(0.108)	(0.083)	(0.077)	(0.065)	(0.057)	(0.057)
Cost-weighted sum of all crimes	−0.213	−0.144	−0.112	−0.099	−0.604	−0.614	−0.586	−0.403	−0.473	−0.471
	(0.054)	(0.071)	(0.034)	(0.041)	(0.184)	(0.228)	(0.147)	(0.179)	(0.157)	(0.157)
Year effects	Yes	-	Yes	-	Yes	-	Yes	-	-	-
State-year effects	No	Yes	No	Yes	No	Yes	No	Yes	Yes	Yes

Note: Sstandard errors are in parentheses.Abbreviations: ASG, Annual Survey of Government; GMM, generalized method of moments; OLS, ordinary least squares; 2SLS, two-stage least squares; UCR, Uniform Crime Report.

TABLE 3 Test of equality of cross-crime elasticities (original dataset).

Crime	Murder	Rape	Robbery	Aggravated Assault	Burglary	Larceny	Motor vehicle Theft	Sum of violent Crimes	Sum of property Crimes
Murder	-	0.193	0.667	0.025	0.035	0.009	0.155	-	0.023
Rape	-	-	0.133	0.442	0.890	0.393	0.674	-	0.686
Robbery	-	-	-	0.001	0.003	0.000	0.081	-	0.000
Aggravated assault	-	-	-	-	0.346	0.868	0.090	-	0.539
Burglary	-	-	-	-	-	0.078	0.219	0.251	-
Larceny	-	-	-	-	-	-	0.004	0.004	-
Motor vehicle theft	-	-	-	-	-	-	-	0.989	-
Sum of violent crimes	-	-	-	-	-	-	-	-	0.046

Note: The table shows the p-values of a t-test of equality between two parameters; the parameter estimates are obtained via generalized method of moments (GMM) by stacking the moment conditions associated with two crimes.

4.3 | Wide replication

Table 4 reports the same results as Table 2 with the extended data set (1962–2019).

The results in Table 4 differ very slightly from Table 2, with the size of the coefficients marginally smaller than those found in Chalfin and McCrary. The notable exceptions here are the elasticities of rape and larceny, which are larger than those calculated with the narrow dataset with OLS (Columns 1–4). Overall, there is very little change in the cost-weighted elasticity of crime when estimated using OLS, with the only exception being Column 4, where it drops from −0.099 to −0.075.

The measurement error-corrected elasticities are reported in Columns 5 to 10, displaying the results of the models estimated using IV (forward and reflected), GMM and OptIV. In case of the 2SLS estimates, we find the elasticities of the

TABLE 4 Estimates of effect of police on crime (extended dataset).

	OLS				2SLS				Pooled Models	
	UCR Measure		ASG Measure		UCR Measure (forward)		ASG Measure (reflected)		GMM	OptIV
Crime	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Murder	−0.252	−0.171	−0.129	−0.103	−0.744	−0.653	−0.513	−0.770	−0.559	−0.558
	(0.068)	(0.087)	(0.047)	(0.054)	(0.268)	(0.342)	(0.202)	(0.259)	(0.207)	(0.207)
Rape	−0.073	−0.084	−0.047	−0.064	−0.270	−0.408	−0.217	−0.251	−0.306	−0.307
	(0.062)	(0.077)	(0.040)	(0.044)	(0.228)	(0.279)	(0.181)	(0.228)	(0.183)	(0.182)
Robbery	−0.165	−0.160	−0.081	−0.072	−0.468	−0.456	−0.488	−0.478	−0.472	−0.472
	(0.043)	(0.040)	(0.030)	(0.026)	(0.174)	(0.169)	(0.126)	(0.122)	(0.102)	(0.102)
Aggravated assault	−0.05	−0.016	0.010	0.0001	−0.058	0.008	−0.0148	−0.048	−0.037	−0.037
	(0.031)	(0.042)	(0.028)	(0.030)	(0.159)	(0.191)	(0.118)	(0.126)	(0.106)	(0.106)
Burglary	−0.061	−0.037	−0.046	−0.042	−0.264	−0.267	−0.182	−0.111	−0.162	−0.162
	(0.039)	(0.033)	(0.024)	(0.020)	(0.140)	(0.125)	(0.116)	(0.097)	(0.079)	(0.079)
Larceny	−0.041	−0.023	−0.017	−0.022s	−0.098	−0.142	−0.120	−0.069	−0.090	−0.090
	(0.029)	(0.024)	(0.020)	(0.016)	(0.113)	(0.099)	(0.084)	(0.071)	(0.058)	(0.058)
Motor vehicle theft	−0.175	−0.113	−0.096	−0.040	−0.554	−0.256	−0.517	−0.339	−0.312	−0.312
	(0.044)	(0.038)	(0.030)	(0.023)	(0.175)	(0.148)	(0.129)	(0.113)	(0.090)	(0.090)
Sum of violent crimes	−0.119	−0.112	−0.057	−0.059	−0.326	−0.377	−0.348	−0.337	−0.349	−0.349
	(0.033)	(0.039)	(0.023)	(0.021)	(0.129)	(0.136)	(0.100)	(0.101)	(0.083)	(0.083)
Sum of property crimes	−0.070	−0.049	−0.038	−0.030	−0.215	−0.191	−0.206	−0.148	−0.162	−0.162
	(0.027)	(0.023)	(0.019)	(0.014)	(0.088)	(0.077)	(0.085)	(0.067)	(0.055)	(0.055)
Cost-weighted sum of all crimes	−0.210	−0.140	−0.100	−0.075	−0.579	−0.474	−0.620	−0.419	−0.437	−0.437
	(0.049)	(0.059)	(0.032)	(0.036)	(0.185)	(0.230)	(0.145)	(0.176)	(0.142)	(0.142)
Year effects	Yes	-	Yes	-	Yes	-	Yes	-	-	-
State-year effects	No	Yes	No	Yes	No	Yes	No	Yes	Yes	Yes

Note: Standard errors are in parentheses.Abbreviations: ASG, Annual Survey of Government; GMM, generalized method of moments; OLS, ordinary least squares; 2SLS, two-stage least squares; UCR, Uniform Crime Report.

TABLE 5 Test of equality of cross-crime elasticities (extended dataset).

Crime	Murder	Rape	Robbery	Aggravated assault	Burglary	Larceny	Motor vehicle theft	Sum of violent crimes	Sum of property crimes
Murder	-	0.379	0.698	0.028	0.046	0.025	0.248	-	0.051
Rape	-	-	0.362	0.141	0.444	0.236	0.953	-	0.423
Robbery	-	-	-	0.000	0.002	0.000	0.166	-	0.001
Aggravated assault	-	-	-	-	0.310	0.664	0.036	-	0.257
Burglary	-	-	-	-	-	0.349	0.105	0.044	-
Larceny	-	-	-	-		-	0.010	0.002	-
Motor vehicle theft	-	-	-	-	-	-	-	0.716	-
Sum of violent crimes	-	-	-	-	-	-	-	-	0.016

Note: The table shows the *p*-values of a *t*-test of equality between two parameters; the parameter estimates are obtained via generalized method of moments (GMM) by stacking the moment conditions associated with two crimes.

various individual crimes to be similar to the ones obtained in Table 2, both in magnitude and sign. An exception is the elasticity of aggravated assault, which has gone from around −0.079 and −0.104 (Columns 6 and 8 in Table 2) to 0.008 and −0.048 in the extended sample. In both cases, though, the coefficients are statistically insignificant. The results are also very similar in both cases, when we compare total violent and property crimes, indicating that the police elasticities of aggregate crimes are robust to time. There is a noticeable fall in the elasticity of the cost-weighted sum of crimes, going from −0.614 to −0.474 when estimated using the forward estimator (Column 6) but a slight rise from −0.403 to −0.419 using the reflected estimator (Column 8). In case of the estimates obtained using the GMM estimator, we again find that elasticities have fallen for most crimes in the extended dataset compared with the narrow, with two notable exceptions. The elasticity of rape has increased from −0.255 to −0.306, while that of larceny has gone up from −0.083 to −0.090. Also in this case and as previously mentioned, the OptIV estimates are in line with the GMM estimates. Overall, the wide replication indicates that Chalfin and McCrary's results are robust temporally.

Table 5 replicates the results seen in Table 3 using the extended dataset. There are some substantial differences, most likely related to the estimate of aggravated assault, which differently from the original dataset case is positive, albeit not statistically significant. As a consequence, the null hypothesis tends to be rejected more often (i.e., for more combinations with other crimes) at standard levels of confidence.

5 | CONCLUSION

In this paper, we replicate Chalfin and McCrary (2018) both in a narrow and wide sense. We find that the key results of the original paper are robust in both cases, as well as to the use of a different software. The narrow replication produces the same estimates of the original paper. We find, though, that standard errors tend to be smaller in our case, producing lower p values for the tests under scrutiny. An estimator of the variance covariance matrix that takes into account degrees of freedom produces more conservative tests that, in the narrow replication, are closer to the original paper results, yet not identical. While there are some differences in the estimated coefficients between the narrow and wide replication, the results support the idea that police is more effective in abating violent crimes (particularly murder) than property crimes. The results also support the idea that elasticity of violent crimes is larger, in absolute value, than those of property crimes. However, it is important to stress the fact that this result is particularly sensitive to the choice of standard errors. The original paper results support the idea that given the effect of police on violent crime, particularly murder, investments on police for this purposes may increase social welfare. Despite the fact that our police elasticity estimate for the crime of murder is lower than that found in the original data, our results, when compared with Chalfin and McCrary's rule of thumb, support this conclusion.

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OPEN RESEARCH BADGES

This article has been awarded Open Data Badge for making publicly available the digitally-shareable data necessary to reproduce the reported results. Data is available at Open Science Framework.

DATA AVAILABILITY STATEMENT

Data and replication codes are available at https://doi.org/10.15456/jae.2023234.1118745048.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of the article.

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