The effects of body-worn cameras on police efficiency: A study of local police agencies in the US.

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Abstract

Do Body-Worn Cameras improve police efficiency? This study answers this question in the context of a sample of local police agencies in the US, where the adoption of BWCs by police agencies has increased significantly in recent years. To estimate the effects of BWCs on police efficiency, I exploited the differences in the adoption of BWCs between agencies that acquired them (”acquirers”) and agencies that deployed them (”deployers”). Using a multiple stage approach, in the first stage I estimated the efficiency of local police agencies using a robust order-m model. In the second stage, I estimated the effects of BWCs using a range of matching estimators and an instrumental variable model. The first stage results show that police agencies could improve their efficiency by 31 percent from 0.76 to 1. The second stage matching and IV estimates suggest that BWCs can help improve police efficiency between eight and 21 percentage points. The effects are larger for those agencies that fully deployed BWCs with their officers. Overall, this study's results support the argument that BWCs can help improve police efficiency.

Keywords: Police, Performance, Efficiency, Data Envelopment Analysis, Matching Estimators, Instrumental Variables.

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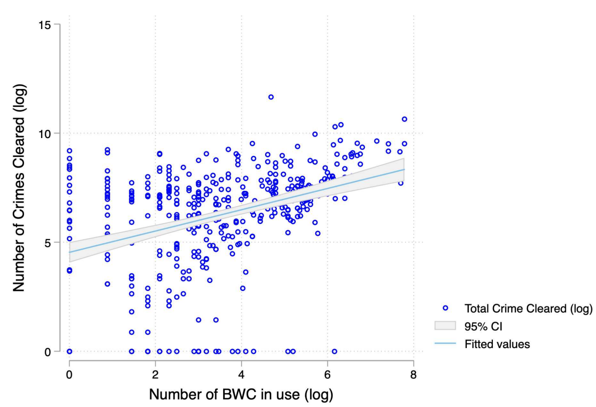
1 Introduction

During the last five years, there has been a dramatic increase in the use of Body-Worn Cameras (BWCs)across law enforcement agencies in the US. Police departments of all sizes have acquired and deployed BWCs to improve their transparency, accountability, and performance (Chapman, 2018). Simultaneously, research on the impact of BWCs on a wide range of law enforcement outcomes has also burgeoned.

A growing body of empirical evidence provides support for the use of this technology to improve various police outcomes, such as accountability, reductions of civilian complaints against police, police-citizen interactions, citizen behavior, among others (Lum, Stoltz, Koper,& Scherer, 2019). However, research on the effects of BWCs on police efficiency, however, remains unexamined. This study addresses some of these questions by estimating the effects of BWCs on the efficiency of local police agencies.

Figure 1 summarizes this study's results. The scatterplot illustrates the correlation between the number of BWCs and a standard police output measured by the percentage of all crimes cleared (Alda, 2014; Barros, 2007). Figure 1 shows a positive correlation between the number of BWCs and higher efficiency levels because agencies with more BWCs appear to clear a higher percentage of crimes.

Figure 1: Bivariate plot of BWCs vs. Crimes Cleared



Notes: Dots represent the number of total crimes cleared by the agency in 2016.

To answer this question, I first estimated police agencies' efficiency using well-known methods to measure efficiency in organizations such as Data

Envelopment Analysis (Charnes & Cooper, 1957). In particular, I employed a robust approach–order-m– (Cazals & Florens, 2007) that corrects for known biases in efficiency measurement, such as the presence of outliers and measurement error.

Secondly, I used a range of matching methods and instrumental variable regression to assess the effect of BWCs on police efficiency between agencies. The use of BWCs by police agencies varies widely. The data show that about 60%[1] of agencies acquired BWCs compared to those that did not. However, not all of the agencies deployed BWCs with their officers. In fact, out of the 60% of agencies that acquired BWCs, 84% implemented a partial or full deployment; and only 40% of the 84% of agencies that deployed BWCs implemented a full deployment with their officers.

I exploited this difference between BWCs "acquirers" and BWCs "deployers" and conceptualized the "acquirers" as Intent to Treat (ITT) and the "deployers" as Treatment on the Treated (TOT). This difference in the adoption of BWCs allowed me to match agencies on a set of organizational and environmental characteristics and assess differences in efficiency levels between "acquirers" and "non-acquirers". Then, I used the "acquirers" (ITT) measure as an instrumental variable to examine differences in efficiency between "deployers[2]" and "acquirers" using LATE[3] analyses.

The findings indicate that BWCs increase police efficiency between seven and 12 percentage points for the ITT analyses and between 10 and 21 percentage points for the LATE estimates. These results support arguments that this technology can improve police efficiency and increase transparency and accountability in police organizations.

This study's results contribute to the rapidly growing literature on the use of BWCs in various ways. First, to my knowledge, this is the first study that examines the effect of BWCs on police efficiency. The current scholarly and policy literature on this topic focuses mainly on measuring the effects of BWCs on outcomes such as transparency, accountability, legitimacy, and on criminal resolution, intelligence gathering, and criminal justice processes outcomes. Some studies have examined outcomes like the speed of criminal resolution or criminal justice processes outcomes. These outcomes

[1] This percentage is based on the final sample used for the analyses, which was 615 local police agencies. See the section on data for more information.

[2] These are the agencies that are assumed compliant and deploy the BWCs.

[3] LATE stands for Local Average Treatment Effects. It is the same as Treatment on the Treated (TOT) effects.

approximate an efficiency measure since criminal investigations, for example, are critical processes of a police production function because they may lead to more crimes cleared (c.f. Morrow, Katz, & Choate, 2016; Owens, Mann, & McKenna, 2014). However, none of these studies use efficiency as their primary focus of research, nor do they produce an actual efficiency estimate. Hence, in addition to examining the effect that BWCs have on police efficiency, I borrow from the literature on productive efficiency and provide an estimate of the levels of police efficiency by using a range and inputs and how their combination contributes to police output (Charnes, Cooper, & Rhodes, 1978).

Second, this study focuses on a sample of 615 police agencies instead of, for example, a single agency or a subset of agencies within a police district where most studies draw their experimental or quasi-experimental evidence from (Kim, 2019; Ariel et al.,2016; Jennings et al.,2017; Harcourt & Ludwig,2006). Although the strength and robustness of results from well-designed experiments are irrefutable, the results of this study are useful because they reveal effects across a larger number of police agencies and help support the results found in experimental and quasi-experimental evaluations.

Finally, this study's results can offer useful operational insights for police agencies in that the deployment of BWCs can assist them in having higher clearance rates because of the faster availability of critical information to help them resolve crimes. In turn, efficiency gains resulting from BWCs can help strengthen other important areas of police operations.

The remainder of the study is structured as follows. Section 2 presents a review of the literature on the use of BWCs, which has focused mainly on experimental evidence assessing BWCs's efficacy on a broad range of outcomes related to officer and citizen behavior, police use of force, civilian complaints, and police accountability, among others. Section 3 presents the data used in the analyses. Section 4 presents and discusses the multiple stage empirical approach to first estimate the efficiency scores and then examine the effects of BWCs using efficiency as the primary outcome of interest. Section 5 presents the results of the preferred model and several robustness tests and sensitivity of the results to the presence of hidden bias. Finally, Section 6 concludes and discusses the limitations.

2 Literature Review

The past five years have witnessed a rapid growth in the literature on the adoption of this technological innovation in law enforcement and its impacts on a wide range of outcomes (Lum, Koper, Merola, Scherer, & Reioux, 2015). Scholars have categorized research on the impact of BWCs around six main areas of study, including impacts on officer behavior and citizen behavior; officer attitudes about BWCs; citizen and community attitudes about police or cameras; criminal investigations; and police organizational structure (Lum, Stoltz, Koper, & Scherer, 2019).

The evidence around the impacts of BWCs police efficiency is still largely understudied. Studies on the effects of BWCs on criminal investigations and crime resolution are perhaps closest to efficiency measurement. Crime investigations are a critical component of a police production function that is often used to measure police organizations' efficiency. For example, the time it takes to clear crimes and the number of resources saved from using BWCs could be interpreted as a measure of efficiency. In fact, previous research on police efficiency has used these variables as outputs in an efficiency model (c.f. Alda, 2014; Alda & Dammert, 2019). Thus, the literature review focuses on the strand of research that more closely approximates the study of efficiency as an outcome, although no studies to date have used a measure of police efficiency as their primary outcome of interest. For a thorough review of available evaluations and research on BWCs, see Lum et al. (2019).

The number of research studies focusing on this proxy of police efficiency, however, is relatively small; it accounts for 6% of all the published research on BWCs to date (Lum et al., 2019), and the results are mixed. Studies have examined the impact of BWCs using the gold standard for evaluations (RCTs) or quasi-experimental approaches, and "before and after" approaches as well as qualitative analyses to support their quantitative findings.

Yokum, Ravishankar, and Coppock (2017) conducted an RCT with more than 2,000 police officers in DC's MPD to examine the impact of BWCs on police complaints, police use of force, policing activity, and judicial outcomes. The latter approximates a measure of efficiency in that it captures the process whereby police arrests are prosecuted in the justice system since the footage produced by BWCs could lead to faster case resolution (Yokum et al., 2017). Overall, the study found very small effects, none of which were statistically significant. One potential explanation for the lack of results is that the researchers did not have access to the full prosecutorial datasets but a dataset on the police department's initial charges.

While the authors offer a range of thorough explanations for the lack of results, the simpler and most likely explanation is that BWCs do not affect the outcomes studied. In the case of the efficiency proxy, the camera footage did not affect judicial outcomes. The study concludes by nuancing the message around the expectations of BWCs as well as encouraging more research on the impact of BWCs (Yokum et al., 2017).

Owens, Mann, and McKenna (2014) also conducted an RCT to measure the impact of BWCs for a sample of 308 police officers in Essex, focusing on reducing bias in the results of incidents attended by officers. The authors also interviewed officers in the treatment group to better understand the operational challenges of BWC deployment.

The findings suggest no differences in the number of incidents sanctioned between officers who wore BWCs and those who did not. However, they suggest significant differences in the type of detected sanction that resulted in criminal charges in the treatment group compared to the control group–81% vs. 72%, respectively.

The study's qualitative part showed that those officers who used BWCs experienced more accountability and paid more attention to their behavior while conducting policing activities. The study concludes with a hypothetical statement that BWCs could be useful in increasing the proportion of detected offenses that result in criminal charges, particularly around domestic abuse cases (Owens et al., 2014).

A recent study used the LEMAS survey to examine the causal impact of BWCs on a range of performance and police use of force outcomes by exploiting the variation in the adoption of BWCs adoption (Kim, 2019). Using the LEMAS BWCs supplement, this study departs from previous research on BWCs. It examines the impact using a national survey of over 1,000 agencies instead of a single agency or group of agencies within a district. The main finding suggests a 54% drop in citizen deaths resulting from police use of force. Furthermore, the study argued that investing in BWCs could yield substantial benefits to police agencies in reducing lawsuits resulting from use of force incidents (Kim, 2019).

Katz and colleagues (2014) and Morrow, Katz, and Choate (2016) use a reflexive comparison[4] approach to examine the impact of BWCs on

[4] Reflexive evaluation or comparison compares the outcomes of the same group before and after

complaints against the police and the processing of domestic violence cases in a precinct of the Phoenix Police Department. The latter outcome could also be considered an efficiency measure. The post-test results for the officers using the camera indicate that cases were more likely to be initiated by the prosecutor compared to pre-test data (40.9% vs. 34.3%). The authors concluded that BWCs could also help improve officers' productivity in addition to reducing civilian complaints.

Finally, Ellis and colleagues (2015) assessed the effects of BWCs in the Isle of Wight in the UK on a range of crime offenses, changes in criminal justice processing, complaints against officers, and officers' views on the use of BWCs. Since all police officers were issued BWCs, the results of the study also used a reflexive comparison approach. The findings related to criminal justice processes on domestic abuse cases suggest an increase in the number of cases from 3 to 21, and in 10 out the 21 cases, there was recorded footage. Furthermore, seven of these 10 cases led to an arrest, and four of the seven cases led to a criminal charge. The authors acknowledge that, because all officers received BWCs, the evaluation did not lend itself to any type of randomization within that police organization. Thus, in the absence of an RCT, their objective was to assess the effectiveness of BWCs from an operational angle for agencies that decide to have an agency-wide rollout of BWCs (Ellis et al., 2015).

Of the five studies discussed above, it is worth noting the differences in the methodological approaches and related findings. Except for Kim's study, the two studies that used more robust evaluation approaches (i.e., RCTs) show null results or limited results compared to those that rely on a reflexive comparison approach, showing significant improvements related to the use of BWCs.

AAlthough informative, reflexive comparison studies have serious limitations in their impact because these approaches attempt to examine program impacts by comparing outcomes before the intervention and after the intervention. The difference between these two periods in time is considered the program's impact.These approaches generally assume that program participants' outcome would have been the same as before the intervention. Research has shown that this is not the case (Gertler, Martinez, Premand, Rawlings, & Vermeersch, 2016), limiting the validity of their findings. It is worth noting that although these studies are limited in their

program participation

statistical validity and their impacts, they still offer lessons learned around the implementation and operationalization of BWCs.

Despite the rapid growth in evaluations on the effect of BWCs on a wide range of outcomes (Lum et al., 2019), research on the effects of BWCs on police efficiency is still nascent. The strand of research presented above, which closely approximates the analysis of efficiency, offers interesting insights on the potential impacts that using BWCs could have in improving police performance. However, as noted above, none of these studies estimate a proper measure of police performance by considering how police inputs contribute to police output production. This study aims to bridge this gap by studying how BWCs contribute, if anything, to improving police performance related to an important police output–clearance rates. The next section discusses the data and methods used in this research.

3 Data

I built a dataset for the year 2016 with information from local police agencies, crime data, and socioeconomic and demographic indicators from a variety of sources. Data on BWCs availability and use and police inputs come from the Law Enforcement Management Survey (LEMAS) (BJS, 2016). The LEMAS survey collects data from various law enforcement agencies in the US, including sheriff, state, and local agencies. For this study's purposes, I limited the sample to local police agencies because they are the law enforcement arm closest to the citizen and where most interaction with law enforcement occurs. Thus, it was important to limit the sample to local police agencies to obtain efficiency estimates that more closely estimate their performance from an efficiency perspective.

Data on police outputs comes from Kaplan's crime dataset (Kaplan, 2020), which contains multi-year concatenated UCR data for state and local police agencies across the US. The socioeconomic and demographic measures come from the American Community Survey (ACS). For this study, I used the ACS 5-year average data to capture changes in municipalities[5]

Before discussing the empirical approach, it is worth noting that

[5]The level of disaggregation in the ACS survey collects information on socioeconomic and demographic conditions that could affect police output production. Using a five-year average is to account for any variation in socioeconomic and demographic factors since these measures may suffer little variation from year to year.

non-parametric efficiency models suffer from potential drawbacks, which require careful consideration because it could lead to biased efficiency estimates. One potential drawback is the presence of missing data. Because the police agency data come from the LEMAS survey there is missing information since not all agencies responded to all question or did not have enough information to answer the question. Thus, to mitigate the effects of missing data on the efficiency estimates, I eliminated from the sample those agencies that had missing information on police inputs before merging it with the UCR and ACS datasets.

Another potential drawback is that non-parametric models require meeting the positivity property; that is, that all values for inputs and outputs have to be positive numbers (>0). If this property is not met, it could render the efficiency model infeasible and yield invalid estimates because there is no possible solution to the linear programming model (Bowlin, 1998).

The literature identifies various ways to deal with this problem in DEA. One is to eliminate those observations with zeroes, and the other one is to add a sufficiently large constant, so the observation meets the positivity property. This approach, while simple in theory, could lead to an additional problem known as translation invariance. Translation invariance occurs when the addition of a constant alters the efficiency frontier and yield biased estimates since not all DEA models are translation invariant (Lovell & Pastor, 1995). Ali and Seiford (1990) developed a model that relaxes the positivity requirement by adding a constant, which causes an affine displacement of the efficiency frontier but does not alter it. In other words, adding a constant would simply be pushing the efficiency frontier further to the right but would not alter the frontier and, thus, not biasing the efficiency estimates. However, this condition would only work if a constant is added to the outputs in variable returns to scale models, and to the inputs and outputs in additive models (Ali & Seiford, 1990; Lovell & Pastor, 1995).

As I show in the methodology section, the used of a variable returns to scale model, allowed me to fulfill the positivity and translation invariance properties by deleting those inputs with values =0 and adding a large enough constant to the outputs. Thus, after pre-processing the data to correct the potential drawbacks described above, the final study sample is comprised of 615 local police agencies.

To estimate the efficiency scores, I followed previous literature on police efficiency and employed a model with four inputs and two outputs (Alda, 2014; Alda, Giménez, & Prior, 2019; Barros, 2007; García-Sánchez, Rodríguez-Domínguez, & Parra-Domínguez, 2013; Gorman & Ruggiero, 2008). The inputs include the number of full-time sworn officers and non-sworn personnel, and the number of marked and unmarked vehicles (see Table 1).

Defining police agencies' output can be challenging as the "bottom line" of policing keeps on expanding and, as a result, its production technology[6] (Moore and Braga, 2003). The challenge is then finding output measures that can capture–to the greatest extent possible[7]–key functions of police agencies. One commonly used measure used as an output in police efficiency studies is the clearance rate (see Barros, 2007; Alda 2014; Alda et al., 2019). The clearance rate captures critical functions of police operations, such as the effectiveness of patrols, speed of police response, and police investigative capacities (Moore and Braga, 2003). Therefore, I approximated police output production by using the total number of index violent and the number of index property crimes[8] cleared by each agency.

Index crimes are a collection of four violent and property crimes that the Federal Bureau of Investigation (FBI) uses to produce their annual crime index. The violent index crimes comprise murder, rape, robbery, and aggravated assault. The property index crimes comprise burglary, theft, motor vehicle theft, and arson[9].

Table 1 presents the summary statistics of the raw data on police inputs and outputs. On average, agencies had 266 sworn officers and 71.3 civilians (non-sworn officers); about 106 marked vehicles and 72 unmarked vehicles. The total number of index property crimes cleared is about twice the total number of index violent crimes cleared with 560.8 and 299, respectively.

4 Methodological Approach

4.1 Conceptual Issues

As indicated above, modern policing has an ever-expanding "bottom line"(Moore and Braga, 2003). Therefore, it is challenging to capture the

[6]This refers to what police agencies do.

[7]This challenge is compounded by limitations in data availability

[8]Efficiency models operate better when using units instead of rates.

[9]For an explanation of these crimes, please visit the FBI. Jacob Kaplan offers useful guidance on the advantages and disadvantages of using index crimes $vis-á-vis$ using these crimes separately.

Table 1: Descriptive Statistics-Input/Output Set

Variable	Obs	Mean	Std. Dev.	Min	Max
Inputs					
Number of Sworn Officers	615	266.15	763.64	5	12042
Number of Non-Sworn Officers	615	71.28	180.26	1	2871
Number of Marked Vehicles	615	105.80	218.71	2	3797
Number of Unmarked Vehicles	615	72.19	140.78	1	1624
Outputs					
Total Index Violent Crime Cleared	615	299.99	795.74	1	12806
Total Index Property Crime Cleared	615	561.82	870.51	1	8291

Source: Own Analysis based on data from BJS(2015) and Kaplan (2020).

police production function in a single model.

Production efficiency theory posits that a decision management unit–police agency in this study–produces the same or higher output levels using the same or fewer inputs, it would be efficient relative to its peers with similar characteristics (Ray, Kumbhakar, & Dua, 2015).

A key aspect of using BWCs is to enable officers to resolve cases faster and reduce paperwork and, as a result, increase the number of crimes cleared (Chapman, 2018). In turn, a higher percentage of crimes cleared would lead to higher police output production. At the same time, if police increase their output production using fewer inputs (i.e., police officers) because BWCs yield more readily available data and information in the investigative process, efficiency would then improve. Furthermore, research has shown that using BWCs can also help officers increase arrests, leading to a quicker resolution of cases (Katz et al., 2014).

While trying to pinpoint how BWCs contribute to improving police efficiency is challenging, using an output measure, such as clearance rates, which encompasses critical police operational activities, can shed light on this issue.

4.2 Analytical Strategy

In this section, I present and discuss the two-staged empirical approach I employed to measure the effect of BWCs on police efficiency. In the first stage, I estimated police efficiency scores using an output oriented model with variable returns to scale. In the second stage, I used a range of matching estimators to assess the effect of agencies that acquired BWCs (”acquirers”) and those agencies that did not acquire BWCs on police efficiency.

Matching helps balance confounding (observable) characteristics between police agencies. However, this approach assumes that the deployment of BWCs is completely exogenous to police efficiency, given a set of observable characteristics. If the exogeneity assumption holds, then the estimates are unbiased (Cavatassi, González-Flores, Winters, Andrade-Piedra, Espinosa, & Thiele, 2011). However, as noted earlier, it is virtually impossible to match police agencies on all the characteristics that can drive the adoption of BWCs. Therefore, it is possible that differences in unobservable characteristics between both groups of agencies exist and could lead to biased estimates.

To address this potential bias, I used instrumental variable regression to examine the effect of BWCs ”deployers” compared to ”acquirers” on police efficiency and reduce potential biases due to unobservable differences between each group. I discuss this issue in more detail in section 4.4.3.

4.3 First Stage

4.3.1 Data Envelopment Analysis

In the first stage, I employed a well-known non-parametric efficiency measurement approach, Data Envelopment Analysis (DEA), to estimate the technical efficiency of local police agencies. DEA models are powerful in estimating organizational efficiency and have distinct advantages compared to, for example, parametric approaches like regression analysis.

First, these models are flexible in that they can accommodate multiple inputs and multiple outputs in the same model, which permits obtaining a more accurate measure of efficiency of complex public-sector organizations like the police. Second, non-parametric techniques provide information on how DMUs can improve their efficiency based on the distance from the best practice efficiency frontier. For example, the results of an output oriented model can indicate to the researcher how much output could an agency increase in order to improve efficiency relative to the best performers while keeping the input set constant. Finally, these techniques do not experience common statistical problems, like multicollinearity or heteroskedasticity, do not require normality in their distribution (Charnes, Cooper, Lewin, & Seiford, 2013), and do not require imposing an ’*a priori*’ functional form as it is the case in regression-based models.

To estimate efficiency, DEA uses the linear combination of DMU's[10] that employ a set of inputs that are under the control of police managers–officers, vehicles– and a set of outputs that the agencies produce–clearance rates, crime prevented. This linear programming combination generates a "best practice" frontier, which captures the firm/s production of maximum output/s given their set inputs relative to their peers in the sample (Charnes et al., 1978). Therefore, a DMU that is on the "best practice"[11] frontier has a value of 1 and indicates that, relative to its peers, it has produced more output using the same or fewer inputs and is, therefore, more efficient.

When using frontier methodologies like DEA or similar linear programming models, defining the type of model orientation is important. There are two main types of models–input and output orientation. An input-oriented model measures how much a unit (police agency) could reduce its inputs while maintaining the same output level. In contrast, an output oriented model measures how much a unit could maximize its output production with the same number of inputs. Therefore, this study employs a DEA output-oriented model with variable returns to scale (VRS). The use of an output orientation is primarily a result of the type of output that defines police agencies' production technology. As discussed above, police agencies' key objective is to call offenders to "account", which is measured by the clearance rate (Moore & Braga, 2003 p.38). Therefore, from the point of view of police production, the clearance rate is an output the police should maximize.

The choice of variable returns to scale is also straightforward since an additional input would not result in a proportional change of the output, as it is the case of constant returns to scale models. This is because police forces generally operate in a non-market environment with imperfect competition and budgetary constraints (Jacobs, Smith & Street, 2006; Giménez, Keith & Prior, 2019). This means that police agencies often operate at an inefficient scale size. In order to support (or reject) the choice of returns to scale, I conducted a non-parametric returns to scale test (Simar & Wilson, 2002). The results rejected the null hypothesis (p<.01) that police agencies operate at an efficient scale[12], and thus, the choice of variable

[10] The DMU (Decision Management Unit) is the unit of analysis. In the case of the current study is local police agencies.

[11] This is the efficiency frontier.

[12] This would mean that a constant returns to scale model would be more appropriate to analyze

returns to scale model is appropriate.

Equation 1 below presents the basic output-oriented DEA model with variable returns to scale.

$$
\begin{aligned}
&\text{Max } \theta \\
&\quad s.t. \\
&\quad \textstyle\sum_{j=1}^{n} \lambda_j x_{ij} = x_{io} && i = 1,2,...,m; \\
&\quad \textstyle\sum_{j=1}^{n} \lambda_j y_{rj} = \theta y_{ro} && r = 1,2,...,s; \\
&\quad \textstyle\sum_{j=1}^{n} \lambda_j = 1 && j = 1,2,...,n. \\
&\quad \lambda_j \geqslant 0 && j = 1,2,...,n.
\end{aligned}
\tag{1}
$$

where DMU_o represents a DMU under analysis, and x_{io} and y_{ro} are the i_{th} input and r_{th} output for DMU_o.The value of θ ranges from 0 (inefficient) to 1 (efficient) . Thus, in an output-oriented model, a value of 1-θ indicates the proportional radial expansion in output that a DMU could achieve given their input set.

Despite their power and flexibility, non-parametric efficiency methods also suffer from limitations. Because of their non-parametric nature, it renders them sensitive to the presence of outliers and measurement error, which could lead to biased estimates. As discussed, given that the data used in this study comes from a survey, it is likely to suffer from measurement error. Furthermore, differences in the size, location, and output produced by the agency will make some agencies outliers[13] compared to the rest of the sample because they perform significantly better than their peers. Therefore, this group of outlier agencies could define the "best practice" efficiency frontier and bias the efficiency scores downward because no other agency can perform better than this group of outliers.

Partial frontier models, such as order-m, enhance efficiency analyses and mitigate some of the common statistical problems in non-parametric techniques like DEA (Cazals, Florens, & Simar, 2002; Simar & Wilson, 2008).

Partial frontier methods operate as follows. To estimate the efficiency score, the order-m algorithm finds an m number of units (police agencies) with similar characteristics in their input/output set so it can calculate how much an agency could produce using the same or fewer inputs than its peers. Therefore, for this particular methodological approach, the choice of m is

efficiency.

[13]In efficiency analyses, outliers are also known as super-efficient or super-performers.

relevant when estimating the efficiency scores (Felder & Tauchmann, 2013). For example, choosing a value of m that is too small would yield a large share of super-efficient observations and, as the value of m increases ($m \to \infty$), the share of super-efficient observations decreases to zero[14]. While there is not a recommended value of m, research suggests choosing a value that would yield 10% of the observations being super-efficient (Bonaccorsi, Daraio & Simar, 2006). For this study, I chose a value of $m = 80$[15], which is considered a large value. In multi-output studies like this, however, the values of m tend to be larger than for single output studies (Felder & Tauchmann, 2013).

Furthermore, the choice of m enables the detection of outliers, which can explain why they are outliers, and whether there are particular characteristics of these agencies that make them outliers as compared to their peers (Daraio & Simar, 2007). Also, because the efficiency frontier is not bounded from above at 1, outperforming agencies (outliers) can yield efficiency scores that are larger than 1 and will not bias efficiency estimates downward. Consequently, the resulting efficiency estimates are closer to the 'true' efficiency frontier compared to a DEA model (Daraio & Simar, 2007). This last feature is potentially useful in studying police forces because their inherent heterogeneity will be reflected in internal organizations, practices, use of resources, and, ultimately, in the production process itself. When performing efficiency analyses of police forces, outliers will emerge, and this technique enables researchers to understand why those observations in the sample perform significantly better than their peers.

4.4 Second Stage-Matching and Instrumental Variable Regression

4.4.1 Matching

In the second stage of this study, I employed a range of matching estimators to assess the effect of BWCs on police efficiency. Since this study is based on survey and administrative data, there is no possible random assignment of agencies into a treatment and a control group. Therefore, to be able to compare the effects of agencies that acquired and deployed BWCs with those that did not, it is important to create groups that are similar based on a set

[14] The maximum efficiency score would be 1.

[15] I conducted efficiency analyses for different values of m. They are not reported here but available upon request.

of observable characteristics.

Matching methods allow the researcher to generate a credible counterfactual–what would the efficiency levels be in the absence of BWCs?–, by creating two comparable groups based on observable characteristics. As a result, the results on the efficiency scores could be attributed to the effect of having adopted BWCs into their policing functions. In addition to being able to generate comparable groups, matching methods reduce selection bias (Cavatassi et al., 2011; Guo Fraser, 2010).

I considered two ways of matching police agencies. The LEMAS survey contains two questions:

- Has your agency acquired body-worn cameras?
- Have body-worn cameras been deployed to officers in your agency?

The first question allowed me to construct an Intent to Treat (ITT) variable comprising all the agencies that acquired BWCs (”acquirers”) regardless of whether or not they deployed them. The second question allowed me to construct a Treatment on the Treated (TOT) measure that captures all agencies that had acquired BWCs and deployed them with their officers (”deployers”). It was possible to generate the latter measure because, according to the responses of the survey, 84% of agencies that acquired BWCs implemented a partial or full deployment.

Scholars argue that studies of BWCs often suffer from potential selection effects. This is because agencies choose to adopt BWCs technology for various reasons, including consent decree, the agency’s interest to improve their performance, accountability and legitimacy, mandated by state law, or organizational characteristics (Maskaly, Donner, Jennings, Ariel, & Sutherland, 2017). For example, larger police agencies may have the budget to adopt and fully implement this type of technology. Nowacki and Willits (2016), however, show that this might not be the case. In their study of organizational drivers of adoption of BWCs, their findings suggest that agencies that are prone to using technology in their operational activity appear more likely to adopt innovative technology schemes such as BWCs. Conversely, the size of the operational budget and the presence of unions appear to hinder the adoption of this type of technology to prevent limitations in police discretion.

Matching methods can help reduce potential selection biases associated with the adoption of BWCs as well as minimizing Type I errors (Guo & Fraser, 2014). However, as discussed earlier, it requires a strong exogeneity assumption and that there are no lurking unobservable variables that could bias the results. Because police agencies are complex organizations (Maguire, 2003), it is virtually impossible to match agencies on all the variables that can influence the adoption of BWCs. I try to address this issue by first matching agencies on a set of exogenous factors and internal organizational characteristics that may influence the adoption of BWCs. Then, I conduct additional tests to check whether the results could be affected by hidden bias due the influence of unobservable characteristics. In the next sections, the study presents the data, the empirical strategy, and the findings.

Although matching algorithms can yield consistent and robust estimates on the effects of BWCs on police efficiency, using only the ITT sample would yield conservative results (Gupta, 2011). This is because the ITT sample includes those agencies that only acquired BWCs and those agencies that deployed BWCs with their officers. This would somewhat underestimate the effect of the actual deployment of BWCs because agencies may acquire BWCs, but might be non-compliant due to limited capacity and organizational management to effectively deploy BWCs (Hyland, 2018; Nowacki & Willits, 2016). To address this issue and obtain a more precise estimate of the effect of BWCs on efficiency from those that deployed BWCs, I used an instrumental variable (IV) regression to conduct the TOT analyses; that is, to examine the effect of BWCs ”deployers” compared to ”non-deployers”.

The TOT analysis yields what is known as the Local Average Treatment Effects (LATE) estimates. Imbens and Angrist (1994) argue that LATE estimates capture the average treatment effect among those exposed to the treatment. In the case of this study, it would capture the effects on the efficiency of those police agencies that deployed BWCs.

4.4.2 Matching Estimators

Matching can be accomplished in several ways. One of the most well-known methods is propensity score matching (PSM). The propensity score defined as the probability of receiving treatment conditional on a set of observable baseline characteristics $ei = Pr(Z_i = 1|X_i)$ (Rosenbaum & Rubin, 1983) (see 2 for the variables used to match agencies).

To estimate the propensity, I used a probit regression model[16] that

[16]Probit and logistic regression models are the most common approaches to estimating the propensity score, although researchers have examined other approaches.

predicts the probability of being treated by an intervention. The propensity score allowed me to create two groups[17] that are similar based on a set of observable covariates, and thus, any differences in the levels of efficiency between these groups can be attributed to the adoption of BWCs.

To examine causal effects using observational data, Rosenbaum and Rubin(1983) argued that two assumptions must be met. The first assumption is the "unconfoundedness assumption",which states that outcomes on the treatment and control groups are independent of participation status conditional on a set of observable covariates (X). This is illustrated with the following equation:

$(Y(0), Y(1)) \perp\!\!\!\perp D|X$

The second assumption that must be met in propensity score matching is the "overlap assumption", which states that observations with the same observable values can be in the treatment or control group (Caliendo & Kopeinig, 2008). The following equation illustrates the overlap condition:

$0 < P(D = 1|X) < 1$

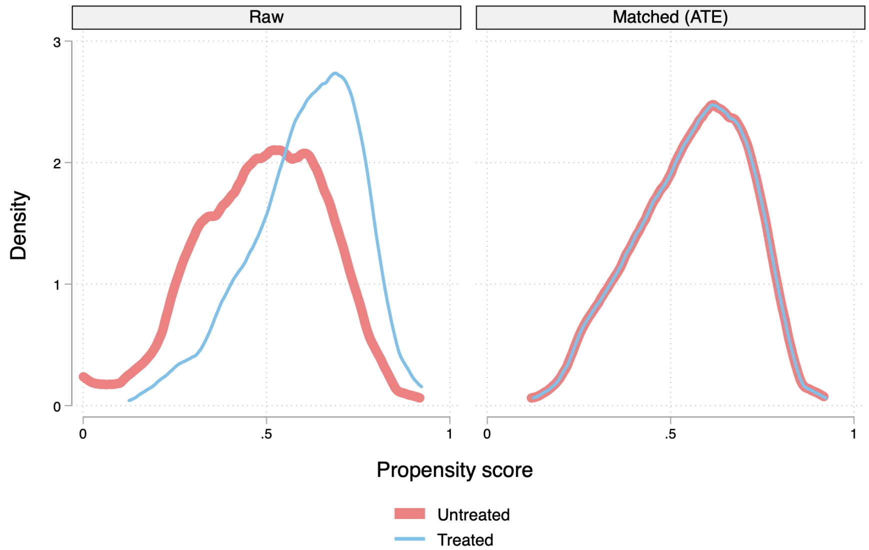
Figure 2 illustrates the density curves before and after matching using the propensity score. After matching, the figure shows no significant differences between the BWCs "acquirers" and "non-acquirers".

Recently, however, matching methods like PSM has sparked a debate about its effectiveness in generating balanced samples to assess impact. For example, King and Nielsen (2019) argue that PSM might achieve the opposite of a balanced sample leading to inefficiency, model dependence, and biased estimates (King & Nielsen, 2019 p.2; Iacus, King & Porro, 2012). To address these shortcomings, the authors proposed a new approach–Coarsened Exact Matching (CEM). This approach finds exact matches, one with that has adopted BWCs and one that has not, instead of matching on a propensity score.

The CEM approach coarsens the exogenous covariates, and divides them into different strata, and finally performs an exact matching within each stratum (King & Nielsen, 2019). One of the major trade-offs of matching is that it requires the researcher to choose which covariates to match agencies. This challenge is evident when using CEM in that if the strata are too

[17] To remind the readers, the two groups I created are: "Acquirers" and "Non-Acquirers" (ITT) and "Deployers" and "Non-Deployers" (LATE)

Figure 2: Density Curves-Unmatched vs. Matched Samples



complex, there is a lower likelihood of finding an exact match and, thus, not being able to conduct any estimation (Vigneri & Lombardini, 2017). A recent study argues that it is possible to conduct matching when using algorithms that do not throw away good matches[18] (Jann, 2017). Thus, for this study, I used a wide range of matching algorithms, including CEM, to check the consistency of the results across various models.

4.4.3 Instrumental Variable Regression

While useful and informative, the ITT analyses may not provide an accurate estimate of BWCs effects on police efficiency since matching methods rely on the assumption that the adoption of BWCs is exogenous to the outcome given a set of observable characteristics X_i as shown in equation (1) above. The main advantage of using an IV approach, when a valid instrument can be found, is that it deals with potential bias from observable and unobservable differences in BWCs adopters and non-adopters. In addition, this method can be used to test the exogeneity assumption used in propensity score matching (Ravallion, 2005). However, relaxing the exogeneity assumption requires finding a valid instrument. A valid instrument has to be strongly correlated with the adoption of BWCs but it

[18] Jann (2017) argues that the results presented by King and colleagues appear to be based on the worst possible matching approach: one to one exact matching without replacement.

cannot be correlated with the error term. It is common in impact evaluation studies to use ITT as an instrument since, in the case of this study, all police agencies that acquired BWCs have the option to deploy them but not every agency does so. As noted earlier, out of 84% of in the sample that deployed BWCs, only 40% deployed them fully with their officers.

An IV approach requires two stages, and each stage is illustrated in the equations below:

$$\text{BWCs}_i = \delta Z_i + \varphi X_i + v_i \qquad \text{(First Stage)}$$
$$\theta_i = \beta X_i + \widehat{BWCs}_i + \epsilon_i \qquad \text{(Second Stage)}$$

where the first stage captures the relationship between instrument Z_i and the adoption of BWCs, and φ captures the relationship between instrument X_i and the adoption of BWCs. In the second stage of the 2SLS model, $\widehat{BWCs}_i$ captures the predicted adoption of BWCs estimated in the first stage. The variables v_i and ϵ_i are the error terms of the first and second stage of the model (Cavataassi et al., 2011).

The first stage is estimated as a linear probability model. Angrist (2000) suggests using this approach when the first stage is a limited dependent variable model and argues that it is consistent and safer since using other models, such as probit/logit, in the first stage is only consistent if the model is exactly correct.

I used two measures of BWCs deployment to conduct the IV analyses. The first variable captures those agencies that implemented a partial deployment of BWCs with their officers. The second variable captures those agencies that permanently deployed BWCs with their officers. I expect the estimates on the full deployment to be larger than the partial deployment because agencies that partially deployed BWCs did it for testing or for a particular assignment and, thus, may not exploit the benefits of this technology.

Table 2 presents the summary statistics of the set of observable characteristics used to match police agencies and used as explanatory variables in the IV regressions. Based on prior research and theoretical tenets in organizational theory, I used a set of exogenous and organizational characteristics that could influence the adoption of BWCs (Alda, 2017; Alda & Dammert, 2019; Alda, Giménez, & Prior, 2019; Barros, 2007; Gorman & Ruggiero, 2008). These include total population, population density, the unemployment rate, the GINI coefficient of income inequality, the poverty rate, the adoption of other technology, the number of prevented civilian complaints against officers; and important organizational structure characteristics, such as the size of the police agency, operational budget; and measures of organizational complexity, such as functional and vertical differentiation. The first of the variables of organizational complexity captures how a police agency assigns tasks within its organization, and it is measured by the number of specialized units in each agency (Nowacki & Willits, 2018; Maguire, 2003). Finally, the second organizational complexity variable measures the hierarchy within an agency, and it is measured by the midpoint salary difference between the highest and lowest rank officer (Nowacki & Willits, 2018; Maguire 2003).

Table 2: Summary Statistics-Observable Characteristics

Variable	Obs	Mean	Std. Dev.	Min	Max
Population Density	615	3738.05	4450.13	217.56	53766.98
Population Estimate (2012)	615	124195.46	259902.74	702	3857799
% Population with less than High School	615	13.46	7.68	0	55.17
Unemployment Rate	615	7.86	3.16	1	22.15
GINI Coefficient of Income Inequality	615	0.45	0.047	0.31	0.62
Poverty Rate	615	16.24	7.74	0.61	43.25
All crimes recorded	615	6645.55	14905.18	0	172294
Civilian Complaints (Reciprocal*)	495	0.17	0.262	0.001	1
Police Agency Size	615	2.62	0.53	1	3
Acquired Car Dashboard Cameras	600	0.71	0.454	0	1
Budget (Ln)	598	16.47	1.417	12.723	20.951
Functional Differentiation	602	4.652	6.690	0	137
Vertical Differentiation	581	69116.98	34697.86	1195	246771

Source: BJS (2015), Kaplan (2020).

* The reciprocal value approximates the total number of civilian complaints prevented by each agency.

5 Results

Table 3 presents the overall efficiency estimates and the estimates disaggregated by police size. The mean efficiency score was 0.76, which indicates that, on average, police agencies that are inefficient relative to the best performers could increase their outputs (crimes cleared) by 31 percent (from 0.76 to 1). Larger and smaller police agencies perform better with efficiency scores between 0.84 and 0.79, respectively. The efficiency score for mid-size police agencies was 0.60, which suggests that they performed worst relative to their larger and smaller peers.

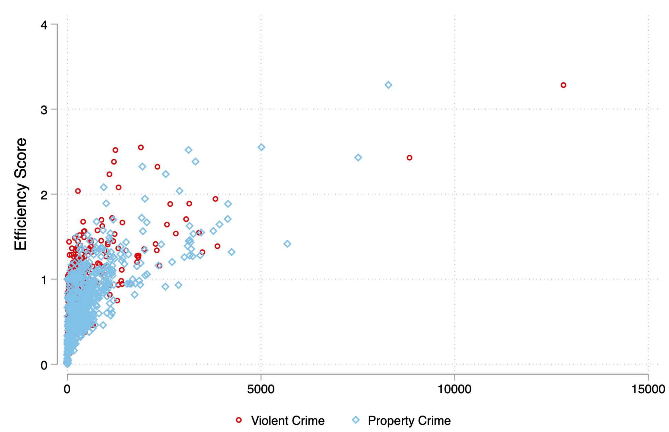
Table 3: Order-m Efficiency Estimates

	Mean	Std. Dev.	Min	Max
Overall Efficiency Score	0.76	0.45	0.00	3.28
Police agency (1-10 Officers)	0.79	0.30	0.25	1.00
Police agency (11-100 Officers)	0.60	0.40	0.01	1.68
Police agency (¿100 Officers)	0.84	0.46	0.00	3.28

Source: Own Analyses using BJS (2015), Kaplan (2020).

Figure 3 illustrates the efficiency results by output. The figure reflects the maximum level of output produced by municipal police forces given their inputs. Police forces with values at or above 1 indicate that they performed better in their output production than the number of m agencies used as comparators.

Figure 3: Order-m Scores



There is, however, significant variation in the levels of efficiency. Out of 615 agencies, only 28 were efficient ($\theta = 1$), which is less than 5% of the sample.These efficient agencies were distributed between small and mid-size. It is worth noting that agencies were very inefficient and others were super-efficient relative to their peers, with efficiency scores as high as 3.3. To interpret this result, an agency with an efficiency score of 3.3 means that it cleared as much as three times more output than a similar m number of peers. Figure 4 in the Annex presents the same results without outlier agencies–$\theta > 1$– which shows more clearly the variation in police performance.

Table 4 presents the estimates on the effects of BWCs on police efficiency using a range of matching estimators and instrumental variable regression. The ITT results that agencies that acquired BWCs have a positive, strong, and statistically significant effect on police efficiency. The estimates are remarkably robust and consistent across model specifications. Improvements in efficiency range from eight to 12 percentage points, depending on the model. The regression adjustment model yielded the smallest coefficient, whereas the mahalanobis distance estimator yielded the largest coefficient. Regression adjusted models in matching estimators add an additional layer of robustness because they reduce additional bias in the covariate balance, ensuring consistency in the estimates, which might explain a slightly smaller estimate in the analyses (Abadie & Imbens, 2011 p.1).

In regards to the IV estimates, the first stage criteria show that the ITT is a valid instrument in the model. It is positive, strong, and statistically significant in the first stage and the instrumented variable is also positive, strong, and highly significant in the second stage. The F-statistic rejects the null hypothesis that the instrument is weak with values well over the accepted 'rule of thumb' threshold of $F > 10$[19] (Cuesta & Alda, 2012). Tests for over-identification and endogeneity assumptions show that there are no over-identifying restrictions and the tests accept the null hypothesis that the instrument can be treated as exogenous. The latter supports the exogeneity assumption needed for the matching estimators (Cavatassi et al., 2011).

As expected, the IV (LATE) estimates are larger in magnitude than the ITT estimates. This is because the LATE estimates capture the effect of BWCs on those agencies that deployed BWCs compared to those agencies

[19] New research questions the use of the $F > 10$ as the rule of thumb for first stage estimates. Lee and colleagues (2020) suggest that F-statistic values should be larger than 104.7 in order to have a true 5% t-ratio test. As Table 4 shows, the first stage F-statistic value is >104.7

that acquired BWCs but did not deploy them. The results indicate that agencies that deployed and permanently deployed BWCs improve their efficiency between 12 and 21 percentage points, respectively. This suggests that controlling for both observable and unobservable characteristics, agencies that deployed BWCs experienced a greater efficiency gains, which supports the argument that the use of BWCs can help improve police efficiency.

Table 4: Regression Results

	DM[1]	PS[2]	RM[3]	NN-3[4]	NN-5[5]	RA-MD[6]	DWPS[7]	CEM[8]	IV[9]	IV-2[10]
Efficiency	0.124***	0.100**	0.103**	0.112**	0.105**	0.079**	0.086**	0.109**	0.125***	0.209***
	(0.033)	(0.042)	(0.040)	(0.044)	(0.044)	(0.038)	(0.037)	(0.040)	(0.043)	(0.072)
Constant								0.669***	-0.427	-0.687
								(0.0314)	(0.503)	(0.522)
Observations	446	446	446	446	446	446	446	415	446	446
R^2								0.02	0.30	0.30

[1] MD = Malahanobis Distance Matching.
[2] PS = Propensity Score Matching.
[3] RM = Propensity Score Ridge Matching.
[4] NN-3 = Nearest Neighbor Matching (3).
[5] NN-5 = Nearest Neighbor Matching (5).
[6] RA-MD = Regression Adjustment.
[7] DWPS = Doubly Weighted Propensity Score Matching.
[8] CEM = Coarsened Exact Matching.

[9] 2SLS Instrumental Variable Regression. First stage F-statistic, 301.3, ($p < .01$).
Kleibergen-Paap rank statistic for cluster-robust 2SLS (null hypothesis is that the equation is under-identified) is rejected.
Stock-Yogo critical value (at 95% confidence) for weak-instrument test statistics (Kleibergen-Paap Wald or CraggDonald F) is 11.38 for maximum bias of IV estimator to be no more than 10% of the maximal IV size (inconsistency) of OLS estimates..

[10] 2SLS Instrumental Variable Regression-2 First stage F-statistic, 268.11, ($p < .01$).
Kleibergen-Paap rank statistic for cluster-robust 2SLS (null hypothesis is that the equation is under-identified) is rejected.
Stock-Yogo critical value (at 95% confidence) for weak-instrument test statistics (Kleibergen-Paap Wald or CraggDonald F) is 16.38 for maximum bias of IV estimator to be no more than 10% of the maximal IV size (inconsistency) of OLS estimates..

Notes:
All matching methods except for CEM were done using Stata's user-written command kmatch (Jann, 2019). The CEM analyses were done using Stata's user-written command CEM (King, 2019). Standard Errors in Parenthesis: significance *10%, **0.05%, ***0.01%

Table 5 presents the predicted efficiency scores for each matching algorithm and the IV models for each group of police agencies; that is, ”acquirers” vs. ”non-acquirers” and ”acquirers” vs. ”deployers”[20]. The predicted efficiency scores are significantly higher, about ten percentage points in the ITT analyses and 20 percentage points larger between ”acquirers” and ”deployers” in the LATE results.

Table 5: Predicted Efficiency Scores

	Non-Acquirers	Acquirers	Acquirers	Deployers*,**
MD	0.678	0.802		
PS	0.694	0.795		
RM	0.693	0.796		
NN-3	0.706	0.818		
NN-5	0.712	0.817		
RA	0.712	0.798		
DWPS	0.718	0.798		
CEM	0.667	0.783		
IV			0.667	0.859
IV-2			0.667	0.860
Avg.	0.695	0.797	0.667	0.859

* Partial Deployment. ** Full Deployment.

5.1 Robustness Checks

Although the results are consistent across matching and IV specifications, the presence of outliers could drive the second stage estimates, given that the proportion of super-efficient agencies is somewhat large. Therefore, to check whether these outliers drive the second stage results, I dropped from the sample those agencies with efficiency scores larger than one and re-estimated the matching and IV models. Table 6 in the Annex presents the result and show, on average, slightly smaller effects, although the LATE estimates are slightly larger than those of the preferred models in Table 4.

As an additional robustness test, I re-estimated the efficiency scores using the reduced sample; that is, the resulting sample after eliminating the

[20]Predicted efficiency scores for deployers include those agencies that partially deployed BWCs and agencies that implemented a full deployment of BWCs.

observations that had efficiency scores > 1[21]. Table 6 in the Annex presents the estimates. The results are still strong and statistically significant across matching estimators and the IV regressions, and do not substantially alter the results of the preferred model specifications (see Table 4). The average of all the effects are slightly larger in the preferred model specifications–0.115 vs. 0.109 percentage points–, which is driven by the ITT estimates.

The reduced sample of the original order-m scores to $\leqslant 1$ shows that BWCs improve efficiency between eight and 11 percentage points for the ITT estimates and 13 to 23 percentage points for the LATE estimates. Conversely, the results on the re-estimated efficiency scores on the reduced sample (see Table 7 in Annex) also show positive, strong, statistically significant effects of BWCs on police efficiency. The magnitude of the coefficients ranges from 13 to 16 percentage points for the ITT estimates and from 20 to 34 percentage points for the LATE estimates. The coefficients are larger likely as a result of the sample being reduced by 166 agencies. Also, the efficiency estimates have changed because the number and type of comparators (agencies) in the sample differ from the base sample and that will invariably influence the generation of the efficiency frontier.

I also conducted the matching and IV analyses on the group of super-efficient police agencies ($\theta > 1$) (see Table 8 in the Annex). These results indicate no effects of BWCs on efficiency among the super-performing agencies[22].

A concern with efficiency estimation is the potential imbalance in the data because of differing magnitudes in inputs and outputs. One way to address this issue in DEA and DEA-based analyses is to mean-normalize the data to ensure similarity in inputs and outputs across units (Sarkis, 2007). I proceeded to mean-normalize the inputs and outputs, estimate the efficiency scores, and use them as the outcome in the matching and IV analyses.

The results indicate that the mean efficiency scores were slightly lower than the preferred model–0.68 compared to 0.76 (see Table 10 in Annex). This reduction in the efficiency scores is likely a result of mean-normalizing the data, which may lessen the influence of outlier agencies in the model. The matching and IV results are smaller in magnitude compared to the preferred models, but are still positive and statistically significant (see Table

[21]The reader should note that even after dropping outlier observations, the analyses will still yield super-efficient observations.

[22]It is worth noting that the N for these analyses is substantially smaller–166– and will likely affect the results.

9 in Annex). For the ITT analyses, the effects of BWCs on police efficiency range from six to ten percentage points, and for the IV models, effects range from 11 to 18 percentage points.

Finally, Table 12 presents the estimates of a basic DEA model using an output-oriented and variable returns to scale model. As discussed above it is plausible that super-efficient agencies may drive the efficiency scores.Therefore, an order-m model would prevent these agencies from setting the efficiency frontier–at = 1 and introduce bias by pushing the rest of the units downward and causing a higher percentage of agencies to become inefficient (Epstein & Henderson, 1989).

The results show a significant drop in efficiency scores to an average score of 0.46 compared to the average of 0.76 in the order-m model. These results help validate the use of an order-m model to obtain more accurate efficiency estimates.

Table 10 presents the matching and IV estimates. Similar to the preferred models, the ITT results indicate that acquiring BWCs has a positive and statistically significant effect on police efficiency. The ITT estimates range from four to seven percentage points[23]. Similarly, the IV estimates are positive and statistically significant, and the size of the coefficients indicate effects ranging from five to 10 percentage points.

5.2 Hidden Bias

I further checked the sensitivity of the results to the presence of hidden bias driven by unobservable factors that could influence the adoption of BWCs. As noted earlier, several internal and external organizational factors and operational factors can influence decision-making in the adoption of BWCs. Therefore, the results should not rule out the possibility of the presence of hidden bias. Gangl and DiPrete (2004) argue that although propensity score matching[24] removes most of the bias due to observable characteristics, it is not a consistent estimator in the presence of hidden bias (DiPrete and Gangl, 2004, p.272).

[23]The regression adjustment estimates are positive but no longer statistically significant at conventional levels ($p < .05$).

[24]Note that propensity score matching is one of several matching algorithms I used in the analyses.

5.2.1 Rosenbaum Bounds

First, I used the Rosenbaum bounds test to examine how the results would be affected in the presence of hidden bias from an unobserved confounding variable. It is worth noting that the presence of hidden bias does not mean the results are invalid; rather, they convey important information on how large the effect of an unobserved variable has to be in order to change the conclusions we infer from the original estimates (DiPrete & Gangl, 2004).

To conduct the analysis, I set the maximum value for Γ, at 1 with increments of 0.1, which are considered appropriate for these type of data (Keele, 2010). Γ values start at 1 and indicate no presence of unobserved confounders, and the p-value should hold if there is no hidden bias. The results suggest that the critical value Γ at which the p-value is no longer statistically significant at conventional values is equal to 1.7 (see Table 15 in the Annex). Thus, in order to question the study's results, an unobserved variable would have to affect the log odds of adoption of BWCs by a factor of 1.7.

5.2.2 Simulated Confounder

Second, I used the simulated confounder approach proposed by Ichino, Mealli, and Nannicini (2008). It assumes that a binary variable $\bigcup$ can be simulated and used as another observable characteristic in the matching analysis. This approach's primary underlying assumption is that the both the observable characteristics and the simulated confounder can influence the adoption of BWCs.

The results show the extent to which the baseline estimates are robust to the failure of the conditional independence assumption. I employed two variables to conduct the simulated confounder analyses on the original outcome variable–police efficiency. The first variable is the size of the police[25], and the second variable is the use of dashboard computers. Both variables are likely associated with the adoption of BWCs. Using a nearest neighbor and kernel matching. Table 16 in the Annex presents the results and show positive and statistically significant effects of both the baseline and the simulated confounder model. The coefficient of 0.11 suggests negligible differences between the baseline and the simulated confounder estimates.

[25] Generating the simulated confounder requires a binary variable. Thus, I generated one where large police agencies take a value of 1 and 0 otherwise.

Furthermore, as recommended in Ichino et al. (2008), both the outcome and selection effects are positive (>1). Like the Rosenbaum bounding approach, these results confirm the robustness of the estimates in the preferred models.

5.2.3 Relative Correlation Restrictions

Finally, I used the relative correlation restrictions (RCR) methodology proposed by Krauth (2016) to construct informative bounds on the effects of BWCs on police efficiency and assess how these estimates behave to deviations from the exogeneity assumptions (Krauth, 2016, p. 2). This methodology assumes a correlation between the adoption of BWCs and the unobserved variables relative to the correlation between the variable of interest and the observed exogenous characteristics. I examined the potential effect of a correlation between the adoption of BWCs and unobservable characteristics that is 0.25, 0.5, 0.75, 1, and twice the correlation size between the adoption of BWCs and the observable characteristics I employed for the matching and IV analyses (Desai & Joshi, 2013).

Table 17 presents the results. The first row shows the OLS regression point estimates in the absence of hidden bias (λ=0), while the remaining rows present the point estimates for up to twice the correlation between the adoption of BWCs and observable characteristics. The RCR results suggest that the point estimates are robust to a weak correlation–0 and 10 percent– between the adoption of BWCs and observable characteristics. However, although the bounds on the effect are narrow and close to the OLS estimate, these are not statistically significant at conventional levels. Furthermore, the RCR bounds show no effect at moderate or large correlations ($0 \leq \lambda \leq 1$) as the bounds include 0. Thus, the RCR results may raise concern on the influence of unobserved confounding variables on the matching estimates.

Overall, the signs and magnitudes of the effects of BWCs on police efficiency are robust to different matching estimators and potential hidden bias.

6 Conclusions and Limitations

In this study I examined the effect of BWCs on police efficiency on a sample of local police agencies in the U.S. in 2016. I conceptualized the adoption of BWCs across local police agencies as those agencies that acquired BWCs and those that deployed them, either partially or fully, with their officers. This differentiation allowed creating an Intent to Treat (ITT) group for all the agencies that acquired BWCs, and a Treatment on the Treated (TOT) group for those agencies that deployed them. To examine the effects of BWCs on police efficiency, I employed a two-stage analytical approach.

In the first stage, I estimated the levels of police efficiency using an efficiency model that is robust to the presence of outliers and measurement error inherent to administrative and survey data. I specifically used an output-oriented and variable returns to scale model because organizations like the police should maximize the output produced (clearance rates) using the same or fewer inputs.

In regards to efficiency, the estimates suggest that police agencies have room for improvement. The efficiency scores range from 0.60 to 0.84, depending on the police agency's size, with an overall mean of 0.76. In other words, on average, police agencies could improve their performance by increasing 31 percent of their output production–clearance rates– using the same or fewer inputs. Furthermore, the results showed that over 100 agencies were deemed super-efficient. This means that these agencies produced output between more than 1 (efficiency score >1), and as much as three times more output than similar peers using the same number of inputs.

In the second stage of the analyses, I employed a range o matching estimators and instrumental variable analyses using the efficiency scores as the outcome of interest. The results indicated a positive, strong, and statistically significant across all matching and IV models. The ITT estimates suggest an improvement in efficiency between seven and 12 percentage points, and the LATE estimates suggest an improvement in efficiency ranging from ten to about 21 percentage points. The effects on efficiency gains substantial. For example, if police can increase efficiency by an average of 11 percentage points[26],the number of crimes cleared would increase from an average of 430 violent and property crimes cleared to 494. While it seems like a small number, it amounts to an average of 64 more crimes cleared annually through the deployment of BWCs.

I also conducted robustness tests and examined the sensitivity of the results to the presence of hidden bias. The robustness tests suggested that, after re-analyzing the models, the presence of outliers does not affect the estimates' strength and robustness, and, if anything, the magnitude of the

[26]This is the average of all the regression coefficients in Table 4.

effects increases from an average of 11 to 12 percentage points. The sensitivity analyses suggest that the models are robustness to the presence of hidden bias except for the relative correlation restrictions approach. The RCR results showed mild robustness to the presence of unobserved factors that could question the robustness of the estimates in the preferred models. Altogether, the findings of this study provide strong support to the argument that the adoption of BWCs can contribute to improving police efficiency, among other aspects of policing.

There are several important caveats to keep in mind with this study. First, the study sample is limited to only local police agencies. The LEMAS survey collects data on a much larger sample of law enforcement agencies and includes the sheriff, county, and state police, among others. Hence, any inferences based on these results should be attributed to local police agencies and not as effects that can be generalized across law enforcement agencies. Furthermore, due to data limitations and missing data for a number of agencies, the data required pre-processing and, as a result, ended up limiting the sample size to 615 local police agencies.

Second, there are limitations in the number and types of police inputs. The LEMAS survey does not contain data on key inputs in a police production function, such as computers, phones, and GPS, among others. The use of technology, paired with adequate organizational and management changes, is important in improving efficiency (Garicano & Heaton, 2010; Milgrom & Roberts, 1990). For this study's purposes, I was able to use two key police inputs, which are the number of police officers and civilian personnel.

Third, I could not capture in the analyses the variation in the adoption of BWCs. The data indicate that some agencies had acquired BWCs 10-15 years ago, and some as recently as 2016, the year the BWCs survey was implemented. Since 2012 the number of police agencies that have adopted BWCs increased by more than 500% from 19 in 2013 to 121 in 2015[27] (see Figure 4 in the Annex). Therefore, it is possible that the early adoption of BWCs may have influenced the efficiency results since they have had more time to use this technology. One possible way to address this issue is to conduct temporal analysis and estimate yearly efficiency levels since the shape of the efficiency frontier, and the units that generate it may change from year to year.

[27] This is based on this study's sample.

Finally, although the study deliberately focused on local police agencies, they still face variation in their technology sets due to differences in organizational structure, financial and human resources, and the operating environment. For example, the efficiency results indicate that the number of super-efficient agencies is somewhat large and driven by mid-size and large agencies. While the methods used in the first and second stages helped address differences between agencies to a great extent[28], there still exists variation in agencies' technology sets, which ultimately affects the generation of the efficiency frontier (O'Donnell, Rao, & Battese, 2008). Thus, modeling the production frontier to account for differences in technology sets would yield efficiency estimates that compared the performance of agencies with peers that have similar technology sets. Unfortunately, sample size limitations did not allow me to model police production function under different technology sets.

Considering these caveats, the findings nevertheless raise a question on the mechanisms through which the use of BWCs improve police efficiency. This is important from an operational point of view. It is challenging to shed light a priori on how BWCs cameras could improve police efficiency, given limitations in data that would allow researchers to model the complexity of a police agency's production function. However, this study offers some potential channels.

Research shows that using BWCs generally contributes to reducing the time needed to clear a crime and send it to the next phase within the criminal justice system (c.f. Morrow et al., 2016). Furthermore, historical research on clearance rates appears to provide support to this argument. Scott and colleagues (2019) suggest average historical trends, despite showing significant stability, there was substantial variation among agencies in their clearance rate performance. Organizational changes and other factors were the primary drivers of variation (Scott, Wellford, Lum & Vovak, 2019).

Another potential channel is the compounding effect that BWCs can have on improved performance through faster police response times. For example, recent evidence suggests that faster police response times can improve crime clearance rates by as much as 4.7% (Vidal & Kirchmeier, 2018). If faster response times alone can lead to higher clearance rates, the enhanced data and information that BWCs can collect could be a key factor in improving clearance rates.

[28]Note that eliminating the super-efficient observations did not substantially alter the estimates.

Of course, organizational factors and external factors beyond police managers' control invariably influence an agency's performance (Alda & Dammert, 2019). As Scott and colleagues(2019) suggested, differences in organizational characteristics could explain variation in clearance rate performance. Hence, having adequate organizational factors conducive to a full deployment of BWCs, and training on proper use of BWCs and other available technology, can positively impact efficiency (Milgrom & Roberts, 1990). Ultimately, however, officers must be compliant in using and exploiting this technology's capabilities to improve law enforcement practices, particularly around maximizing output production while using the same or fewer resources.

Improving police organizations' efficiency can significantly impact budgetary allocations in local government and police organizations to ensure proper allocation of resources to maximize service delivery. Taken together, the results of this study shed light on the effects that this technology has on police efficiency. It will be important to expand on this strand of research within the growing body of literature on the use of BWCs by law enforcement agencies.

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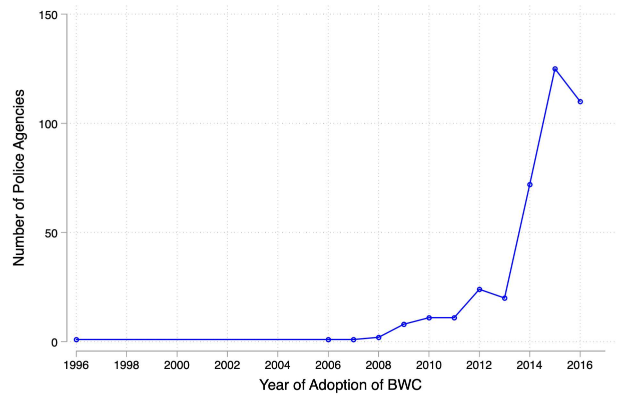
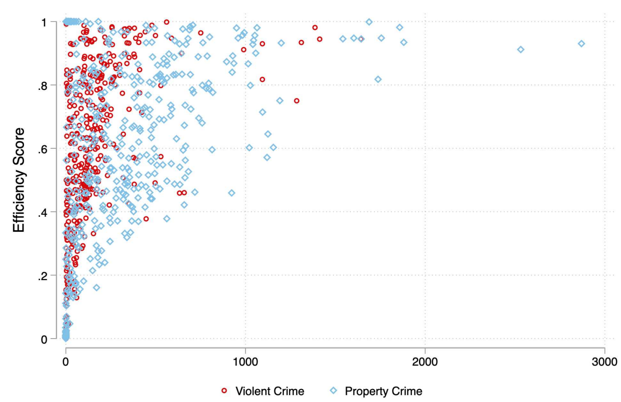
Annex-Supplementary Figures and Tables

Figure 4: Yearly Adoption of BWCs



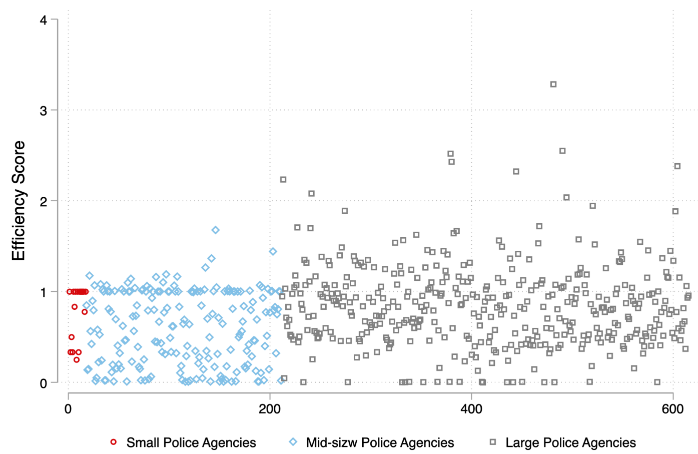
Notes: Source: Own Analyses using BJS (2015), Kaplan (2020).

Figure 5: Order-m Scores



Notes: Order-m efficiency scores without outlier agencies.

Figure 6: Efficiency by Agency Size



Notes: Order-m efficiency scores by agency size.

Figure 7: Bivariate Plot: Efficiency Scores vs. Efficiency Scores-Mean Normalized

Table 6: Results-Sample with Efficiency Scores $\leqslant 1$

	DM[1]	PS[2]	RM[3]	NN-3[4]	NN-5[5]	RA-MD[6]	DWPS[7]	CEM[8]	IV[9]	IV-2[10]
Efficiency	0.111***	0.094**	0.093**	0.0790*	0.090**	0.0827*	0.096***	0.0850***	0.133***	0.230***
	(0.0339)	(0.0377)	(0.0379)	(0.0413)	(0.0397)	(0.0424)	(0.0367)	(0.0327)	(0.0390)	(0.0675)
Constant								0.517***	0.823	0.447
								(0.0252)	(0.557)	(0.582)
Observations	320	320	320	320	320	320	320	316	320	320
R^2								0.02	0.13	0.12

1 MD = Malahanobis Distance Matching.
2 PS = Propensity Score Matching.
3 RM = Propensity Score Ridge Matching.
4 NN-3 = Nearest Neighbor Matching (3).
5 NN-5 = Nearest Neighbor Matching (5).
6 RA-MD = Regression Adjustment.
7 DWPS = Doubly Weighted Propensity Score Matching.
8 CEM = Coarsened Exact Matching.
9 2SLS Instrumental Variable Regression. First stage F-statistic, 760.27 ($p < .01$).
Kleibergen-Paap rank statistic for cluster-robust 2SLS (null hypothesis is that the equation is under-identified) is rejected.
Stock-Yogo critical value (at 95% confidence) for weak-instrument test statistics (Kleibergen-Paap Wald or CraggDonald F) is 11.38 for maximum bias of IV estimator to be no more than 10% of the maximal IV size (inconsistency) of OLS estimates.

10 2SLS Instrumental Variable Regression-2 First stage F-statistic, 162.20, ($p < .01$).
Kleibergen-Paap rank statistic for cluster-robust 2SLS (null hypothesis is that the equation is under-identified) is rejected.
Stock-Yogo critical value (at 95% confidence) for weak-instrument test statistics (Kleibergen-Paap Wald or CraggDonald F) is 16.38 for maximum bias of IV estimator to be no more than 10% of the maximal IV size (inconsistency) of OLS estimates.

Notes: All matching methods except for CEM were done using Stata's user-written command kmatch (Jann, 2019). The CEM analyses were done using Stata's user-written command CEM (King, 2019). Standard Errors in Parenthesis: significance *10%, **0.05%, ***0.01%

Source: Own analysis using BJS (2015), Kaplan (2020), and US Census Bureau (2017).
Estimates are based on 1,000 bootstrap replications.

Table 7: Results - Re-Analyses of Efficiency Scores and BWCs Effects

	DM[1]	PS[2]	RM[3]	NN-3[4]	NN-5[5]	RA-MD[6]	DWPS[7]	CEM[8]	IV[9]	IV-2[10]
Efficiency	0.167***	0.151***	0.153***	0.110***	0.048***	0.032***	0.049***	0.0.050**	0.196***	0.338***
	(0.0462)	(0.0442)	(0.0456)	(0.0512)	(0.0262)	(0.0263)	(0.0262)	(0.0259)	(0.0496)	(0.0870)
Constant								0.360***	0.302	-0.252
								(0.0204)	(0.641)	(0.677)
Observations	320	320	320	320	446	446	446	416	320	320
R^2								0.01	0.23	0.20

[1] MD = Malahanobis Distance Matching.
[2] PS = Propensity Score Matching.
[3] RM = Propensity Score Ridge Matching.
[4] NN-3 = Nearest Neighbor Matching (3).
[5] NN-5 = Nearest Neighbor Matching (5).
[6] RA-MD = Regression Adjustment.
[7] DWPS = Doubly Weighted Propensity Score Matching.
[8] CEM = Coarsened Exact Matching.
[9] 2SLS Instrumental Variable Regression. First stage F-statistic, 760.27, ($p < .01$).
Kleibergen-Paap rank statistic for cluster-robust 2SLS (null hypothesis is that the equation is under-identified) is rejected.
Stock-Yogo critical value (at 95% confidence) for weak-instrument test statistics (Kleibergen-Paap Wald or CraggDonald F) is 11.38 for maximum bias of IV estimator to be no more than 10% of the maximal IV size (inconsistency) of OLS estimates..

[10] 2SLS Instrumental Variable Regression-2 First stage F-statistic, 162.20, ($p < .01$).
Kleibergen-Paap rank statistic for cluster-robust 2SLS (null hypothesis is that the equation is under-identified) is rejected.
Stock-Yogo critical value (at 95% confidence) for weak-instrument test statistics (Kleibergen-Paap Wald or CraggDonald F) is 16.38 for maximum bias of IV estimator to be no more than 10% of the maximal IV size (inconsistency) of OLS estimates. .

Notes: All matching methods except for CEM were done using Stata's user-written command kmatch (Jann, 2019). The CEM analyses were done using Stata's user-written command CEM (King, 2019). Standard Errors in Parenthesis: significance *10%, **0.05%, ***0.01%

Source: Own analysis using BJS (2015), Kaplan (2020), and US Census Bureau (2017).
Estimates are based on 1,000 bootstrap replications.

Table 8: Results - Robustness Analyses-Outlier Agencies

	DM[1]	PS[2]	RM[3]	NN-3[4]	NN-5[5]	RA-MD[6]	DWPS[7]	CEM[8]	IV[9]	IV-2[10]
Efficiency	0.0661	0.0208	0.0145	0.0391	0.0355	0.0273	-0.0147	0.000814	0.0501	0.0764
	(0.0548)	(0.0529)	(0.0575)	(0.0517)	(0.0507)	(0.117)	(0.0521)	(0.0851)	(0.0463)	(0.0713)
Constant								1.302***	-0.933	-1.029
								(0.0721)	(0.711)	(0.738)
Observations	126	126	126	126	126	126	126	71	126	126
R^2								0.00	0.44	0.42

[1] MD = Malahanobis Distance Matching.
[2] PS = Propensity Score Matching.
[3] RM = Propensity Score Ridge Matching.
[4] NN-3 = Nearest Neighbor Matching (3).
[5] NN-5 = Nearest Neighbor Matching (5).
[6] RA-MD = Regression Adjustment.
[7] DWPS = Doubly Weighted Propensity Score Matching.
[8] CEM = Coarsened Exact Matching.
[9] 2SLS Instrumental Variable Regression. First stage F-statistic, 742.95, ($p < .01$).
Kleibergen-Paap rank statistic for cluster-robust 2SLS (null hypothesis is that the equation is under-identified) is rejected.
Stock-Yogo critical value (at 95% confidence) for weak-instrument test statistics (Kleibergen-Paap Wald or CraggDonald F) is 16.38 for maximum bias of IV estimator to be no more than 10% of the maximal IV size (inconsistency) of OLS estimates..

[10] 2SLS Instrumental Variable Regression-2 First stage F-statistic, 117.03, ($p < .01$).
Kleibergen-Paap rank statistic for cluster-robust 2SLS (null hypothesis is that the equation is under-identified) is rejected.
Stock-Yogo critical value (at 95% confidence) for weak-instrument test statistics (Kleibergen-Paap Wald or CraggDonald F) is 16.38 for maximum bias of IV estimator to be no more than 10% of the maximal IV size (inconsistency) of OLS estimates. .

Notes: All matching methods except for CEM were done using Stata's user-written command kmatch (Jann, 2019). The CEM analyses were done using Stata's user-written command CEM (King, 2019). Standard Errors in Parenthesis: significance *10%, **0.05%, ***0.01%

Source: Own analysis using BJS (2015), Kaplan (2020), and US Census Bureau (2017).
Estimates are based on 1,000 bootstrap replications.

Table 9: Results - Robustness Analyses-Normalized Input/Output Set

	DM[1]	PS[2]	RM[3]	NN-3[4]	NN-5[5]	RA-MD[6]	DWPS[7]	CEM[8]	IV[9]	IV-2[10]
Efficiency	0.103***	0.0892**	0.0919**	0.0969**	0.0916**	0.0684**	0.0763**	0.0940***	0.110***	0.184***
	(0.0355)	(0.0374)	(0.0383)	(0.0376)	(0.0364)	(0.0343)	(0.0379)	(0.0344)	(0.0379)	(0.0632)
Constant								0.608***	0.0471	0.182
								(0.0270)	(0.432)	(0.446)
Observations	446	446	446	446	446	446	446	416	446	446
R^2								0.02	0.24	0.24

[1] MD = Malahanobis Distance Matching.
[2] PS = Propensity Score Matching.
[3] RM = Propensity Score Ridge Matching.
[4] NN-3 = Nearest Neighbor Matching (3).
[5] NN-5 = Nearest Neighbor Matching (5).
[6] RA-MD = Regression Adjustment.
[7] DWPS = Doubly Weighted Propensity Score Matching.
[8] CEM = Coarsened Exact Matching.
[9] 2SLS Instrumental Variable Regression. First stage F-statistic, 1271.66, ($p < .01$).
Kleibergen-Paap rank statistic for cluster-robust 2SLS (null hypothesis is that the equation is under-identified) is rejected.
Stock-Yogo critical value (at 95% confidence) for weak-instrument test statistics (Kleibergen-Paap Wald or CraggDonald F) is 16.38 for maximum bias of IV estimator to be no more than 10% of the maximal IV size (inconsistency) of OLS estimates..

[10] 2SLS Instrumental Variable Regression-2 First stage F-statistic, 246.22, ($p < .01$).
Kleibergen-Paap rank statistic for cluster-robust 2SLS (null hypothesis is that the equation is under-identified) is rejected.
Stock-Yogo critical value (at 95% confidence) for weak-instrument test statistics (Kleibergen-Paap Wald or CraggDonald F) is 16.38 for maximum bias of IV estimator to be no more than 10% of the maximal IV size (inconsistency) of OLS estimates. .

Notes: All matching methods except for CEM were done using Stata's user-written command kmatch (Jann, 2019). The CEM analyses were done using Stata's user-written command CEM (King, 2019). Standard Errors in Parenthesis: significance *10%, **0.05%, ***0.01%

Source: Own analysis using BJS (2015), Kaplan (2020), and US Census Bureau (2017).
Estimates are based on 1,000 bootstrap replications.

Table 10: Order-m Efficiency Estimates- Mean Normalized

	Mean	Std. Dev.	Min	Max
Overall Efficiency Score	0.68	0.27	0.0003	2.40
Police agency (1-10 Officers)	0.78	0.30	0.25	1.00
Police agency (11-100 Officers)	0.57	0.38	0.006	1.16
Police agency (>100 Officers)	0.73	0.36	0.0003	2.40

Source: Own Analyses using BJS (2015), Kaplan (2020).

Table 11: Predicted Efficiency Scores- Mean Normalized

	Non-Acquirers	Acquirers	Acquirers	Deployers*,**
MD	0.618	0.721		
PS	0.625	0.714		
RM	0.623	0.715		
NN-3	0.636	0.733		
NN-5	0.641	0.732		
RA	0.646	0.714		
DWPS	0.63	0.706		
CEM	0.607	0.701		
IV				0.607 0.7619
IV-2				0.607 0.771
Avg.	0.62825	0.717 0.607 0.76645		

Source: Own Analyses using BJS (2015), Kaplan (2020), and US Census Bureau (2017).
* Partial Deployment. ** Full Deployment.

Table 12: Results - Robustness Analyses using a DEA model

	DM[1]	PS[2]	RM[3]	NN-3[4]	NN-5[5]	RA-MD[6]	DWPS[7]	CEM[8]	IV[9]	IV-2[10]
Efficiency	0.0732***	0.0524**	0.0557**	0.0542**	0.0484*	0.0322	0.0481*	0.0501*	0.0584**	0.0975**
	(0.0251)	(0.0266)	(0.0271)	(0.0264)	(0.0262)	(0.0263)	(0.0260)	(0.0259)	(0.0283)	(0.0473)
Constant								0.360***	0.383	0.262
								(0.0203)	(0.338)	(0.348)
Observations	446	446	446	446	446	446	446	415	446	446
R^2								0.01	0.19	0.19

[1] MD = Malahanobis Distance Matching.
[2] PS = Propensity Score Matching.
[3] RM = Propensity Score Ridge Matching.
[4] NN-3 = Nearest Neighbor Matching (3).
[5] NN-5 = Nearest Neighbor Matching (5).
[6] RA-MD = Regression Adjustment.
[7] DWPS = Doubly Weighted Propensity Score Matching.
[8] CEM = Coarsened Exact Matching.
[9] 2SLS Instrumental Variable Regression. First stage F-statistic, 1271.66, ($p < .01$).
Kleibergen-Paap rank statistic for cluster-robust 2SLS (null hypothesis is that the equation is under-identified) is rejected.
Stock-Yogo critical value (at 95% confidence) for weak-instrument test statistics (Kleibergen-Paap Wald or CraggDonald F) is 16.38 for maximum bias of IV estimator to be no more than 10% of the maximal IV size (inconsistency) of OLS estimates..

[10] 2SLS Instrumental Variable Regression-2 First stage F-statistic, 246.22, ($p < .01$).
Kleibergen-Paap rank statistic for cluster-robust 2SLS (null hypothesis is that the equation is under-identified) is rejected.
Stock-Yogo critical value (at 95% confidence) for weak-instrument test statistics (Kleibergen-Paap Wald or CraggDonald F) is 16.38 for maximum bias of IV estimator to be no more than 10% of the maximal IV size (inconsistency) of OLS estimates. .

Notes: All matching methods except for CEM were done using Stata's user-written command kmatch (Jann, 2019). The CEM analyses were done using Stata's user-written command CEM (King, 2019). Standard Errors in Parenthesis: significance *10%, **0.05%, ***0.01%

Source: Own analysis using BJS (2015), Kaplan (2020), and US Census Bureau (2017).
Estimates are based on 1,000 bootstrap replications.

Table 13: DEA Efficiency Estimates

	Mean	Std. Dev.	Min	Max
Overall Efficiency Score	0.41	0.27	0.0001	1.00
Police agency (1-10 Officers)	0.65	0.37	0.05	1.00
Police agency (11-100 Officers)	0.36	0.30	0.002	1.00
Police agency (>100 Officers)	0.41	0.24	0.0001	1.00

Source: Own Analyses using BJS (2015), Kaplan (2020).

Table 14: Predicted Efficiency Scores-DEA Model

	Non-Acquirers	Acquirers	Acquirers	Deployers*,**
MD	0.361	0.434		
PS	0.368	0.420		
RM	0.366	0.422		
NN-3	0.372	0.426		
NN-5	0.377	0.425		
RA	0.389	0.421		
DWPS	0.374	0.422		
CEM	0.359	0.409		
IV			0.358	0.446
IV-2			0.358	0.447
Avg.	0.370	0.422	0.358	0.446

Source: Own Analyses using BJS (2015), Kaplan (2020), and US Census Bureau (2017).
* Partial Deployment. ** Full Deployment.

Table 15: Rosenbaum Bounds

Γ	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1.0	0.0000	0.0000	0.1490	0.1490	0.0796	0.2120
1.1	0.0002	0.0000	0.1310	0.1664	0.0595	0.2295
1.2	0.0009	0.0000	0.1133	0.1822	0.0439	0.2451
1.3	0.0037	0.0000	0.0971	0.1961	0.0277	0.2595
1.4	0.0114	0.0000	0.0815	0.2106	0.0127	0.2724
1.5	0.0286	0.0000	0.0667	0.2221	-0.0017	0.2850
1.6	0.0602	0.0000	0.0557	0.2346	-0.0137	0.2956
1.7	0.1099	0.0000	0.0445	0.2445	-0.0252	0.3063
1.8	0.1785	0.0000	0.0342	0.2536	-0.0371	0.3147
1.9	0.2636	0.0000	0.0233	0.2631	-0.0477	0.3247
2.0	0.3599	0.0000	0.0138	0.2713	-0.0583	0.3335

Γ- Log odds of differential assignment due to unobserved factors.
sig+-Upper bound significance level.
sig--Lower bound significance level.
t-hat+-Upper bound Hodges-Lehmann point estimate.
t-hat--Lower bound Hodges-Lehmann point estimate.
CI+-Upper bound confidence interval (a= .95).
CI--Lower bound confidence interval (a= .95).
Source: Own analysis using BJS (2015), Kaplan (2020), and US Census Bureau (2017).

Table 16: Simulated Confounder

Police Size	Baseline Estimate	Simulated Estimate	Outcome Effect	Selection Effect
Kernel Matching	0.114***	0.112***	1.44	1.525
Nearest Neighbor	0.057	0.106	1.576	1.538
Dashboard Cameras				
Kernel Matching	0.114***	0.114***	1.081	1.833
Nearest Neighbor	0.056	0.11	1.045	1.829

Source: Own analysis using BJS (2015), Kaplan (2020), and US Census Bureau (2017).
Estimates are based on 1,000 bootstrap replications.

Table 17: Relative Correlation Restrictiions

	ITT	TOT
OLS point estimate ($\lambda = 0$)	0.106***	0.110***
(95% CI)	(0.03,0.178)	(0.04,0.183)
Bounds, $0 \leqslant \lambda \leqslant 0.1$	[0.112,0.260]	[0.29,0.444]
(95% CI)	(0.09,0.106)	(0.10,0.112)
Bounds, $0 \leqslant \lambda \leqslant 0.25$	[-0.212,0.260]	[-0.409, 0.444]
(95% CI)	(0.065,0.106)	(0.082,0.112)
Bounds, $0 \leqslant \lambda \leqslant 0.5$	[-0.405,0.260]	[-0.611,0.444]
(95% CI)	(0.206,0.106)	(0.050,0.112)
Bounds, $0 \leqslant \lambda \leqslant 1$	[-0.920,0.260]	[-1.00,0.444]
(95% CI)	(-0.081,0.106)	(-0202,0.112)
Bounds, $0 \leqslant \lambda \leqslant 2$	[-3.10,0.260]	[-1.883,0.444]
(95% CI)	(-0.390,0.106)	(-0.204,0.112)
λ_∞	2.82	3.34
$\lambda(0)$	0.61	2.94
Minimum λ for which bounds include zero	0.61	2.94

Source: Own analysis using BJS (2015), Kaplan (2020), and US Census Bureau (2017).

Notes: λ is the assumed correlation between the treatment and the observed variables. Bounds reflect the estimates of the adoption of BWCs (ITT and TOT) on police efficiency. Intervals in brackets are the estimated rcr bounds and the intervals in parenthesis are 95% asymptotic confidence intervals.