Empirical Bayes Counterfactuals in Poisson Regression with an Application to Police Use of Deadly Force*

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Abstract

This paper uses an Empirical Bayes approach to estimate the conditional mean function of a Poisson regression model, evaluated at *counterfactual* values of time-invariant unobserved covariates. The application that motivates and illustrates the methods developed herein is the use of deadly force by police officers in the United States. We construct a yearly panel of lethal encounters covering the period 2013-2018, focusing on law enforcement agencies, rather than cities or states. We estimate counterfactuals for the nation's ten largest police departments by population served, and show that feasible changes in both observed and unobserved characteristics could result in a significant reduction in lethal encounters.

Keywords: Empirical Bayes Methods, Poisson Regression, Police Use of Deadly Force.

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1 Introduction

An integer-valued outcome variable, Y_{jt}, is observed for $j = 1 \ldots J$ different units during $t = 1 \ldots T$ periods. The panel is short (in that $T << J$), and the outcome variable at each period—conditional on covariates—is assumed to have a Poisson distribution. This paper describes the statistical model's conditional mean function when evaluated at *counterfactual* values of the covariate vector. While this is a simple problem when all the covariates are observed, there are a number of challenges when the main parameter of interest involves counterfactual changes in variables that are not available to the econometrician. We address these challenges for the case in which the unobserved covariates are time invariant.

The empirical application that illustrates and motivates the methods developed here is the use of deadly force by police officers in the United States. This issue is of paramount social importance, since over a thousand civilians die at the hands of law enforcement officials every year. We construct a yearly panel of lethal encounters covering the period 2013-2018, focusing on law enforcement agencies, rather than cities or states. Our agency-level data set includes 7,585 law enforcement agencies (not only those that have been associated with police homicides), along with several time-varying and time-invariant attributes: the population served, the number of sworn officers relative to the population served, the murder rate, the poverty rate, population demographics, the county level frequency of gun deaths, state laws on the use of deadly force, and state laws protecting police from misconduct allegations.

Despite our efforts to collect reliable, comprehensive data on agency-level characteristics, there are a number of important omitted variables which we believe are relatively stable over time. Data for agencies' selection practices, training, promotion standards, disciplinary procedures, and organizational culture are scarce or nonexistent.[1] Anecdotal evidence suggests that these variables are important predictors of police homicides and some departments are "unusually quick to use force, slow to back down, and make the habit of releasing selective

[1]The Law Enforcement Management and Administrative Statistics (LEMAS) data set contains useful information on many of these factors but covers only about 3,000 agencies, and is compiled once every three years. We hope to exploit LEMAS in future work.

or misleading information about what happened" (Oppel, 2018).[2] Respected criminologists have also argued that management and cultural variables within police departments are important reasons why agencies differ in the rate at which they engage in police homicides (Sherman et al., 1986; Zimring, 2017; Sherman, 2018). And at least two studies have shown that changes in management procedures in specific cities were followed by decreases in police homicides, and argued that changes in observables were unable to account for these decreases (Sherman, 1983; Fyfe, 1979).

To give a concrete idea of the hypothetical questions we would like to answer, consider the following two examples. First, what would happen to the expected number of lethal encounters involving the Phoenix Police Department if this department were to adopt the selection practices, training, and organizational culture of the New York City Police Department? Second, what would happen to the expected number of police homicides by the New York City Police Department if the size of its force were reduced? The first is a counterfactual question in which we would like to evaluate the conditional mean function of lethal encounters using the observable characteristics of the Phoenix Police Department and the *unobservable* characteristics of the New York Police Department. The second is a counterfactual question in which we would like to evaluate the conditional mean function of lethal encounters using both the observable and unobservable characteristics of the New York City Police Department, but where we consider one or more counterfactual values for the size of its force.

We answer these questions using Empirical Bayes methods (Robbins, 1956, 1964; Efron, 2010).[3] To understand our approach consider the case in which there is only one unobserved covariate that enters into the conditional mean of the Poisson distribution multiplicatively.

[2] Since we observe many more characteristics of the populations policed by the departments than of the departments themselves, we believe that the most important unobserved variables are characteristics of departments rather than populations. But there may be important unobserved characteristics of populations also, such as attitudes towards law enforcement agents.

[3] Empirical Bayes methods and hierarchical Bayes models have already been used in the statistical analysis of police homicides (Schwartz and Jahn, 2020). In this paper, we are more explicit about the parameters of interest and use cross-sectional variation to dispense with strong parametric assumptions about unobserved components.

Suppose the econometrician knows i) the joint distribution of the observed and unobserved covariates, and ii) the slope coefficients of the observed covariates in the conditional mean function. Under quadratic loss and some standard conditions, the best estimator of the counterfactual involving the unobserved covariate of unit j uses its *posterior mean* as a surrogate. That is, instead of evaluating the conditional mean function at the unobserved covariate of unit j, the conditional mean function is evaluated at the expected value of the unobserved covariate given the available data for unit j.

In practice the joint distribution of observed and unobserved characteristics is unknown. We exploit the Poisson likelihood function to derive a panel data analog of the celebrated formula of Robbins (1956), where the posterior mean is expressed in terms of the cross-sectional distributions of outcomes and covariates, and also on the slope coefficients of the observed variables. Under assumptions that we shall spell out clearly—and that closely follow the work of Honoré and Kesina (2017)—the parameters that enter this formula can be estimated consistently. Plugging in these estimated parameters transforms Robbins' formula into an Empirical Bayes estimator. It is then possible to quantify the sampling uncertainty in the estimation of the counterfactuals by using delta-method/bootstrap arguments. Similar applications of Empirical Bayes methods that motivated the analysis in this paper, but in the context of normally distributed errors, appear in Liu, Moon and Schorfheide (2020), Liu (2020), and Gu and Koenker (2020). Other recent applications of Empirical Bayes methods are Angrist et al. (2020) and Arnold, Dobbie and Hull (2020).

We thus estimate *pairwise* counterfactuals for lethal encounters that involve changing the unobserved covariates of agency j by those of agency j'. We focus on the ten largest police departments, ranked by population served. These are the primary departments serving the cities of New York, Los Angeles, Chicago, Houston, Phoenix, Philadelphia, San Antonio, San Diego, and Dallas, along with the Las Vegas Metro Police Department.[4] Together these

[4]Each of these departments served over 1.35 million people in 2018. Some sheriff's offices are of comparable size, but we exclude them from our analysis since they are very heterogeneous with respect to duties performed.

departments were involved in 548 on-duty deadly force incidents over 2013-2018, which is about 14% of the total number associated with police departments in the nation as a whole.[5]

Our data and methods yield the following results. When we order these ten departments in terms of the estimated effect of their unobserved characteristics on lethal encounters, we find the Phoenix Police Department to be the most deadly, and the New York City Police Department to be the least. Our Empirical Bayes approach suggests—with 90% confidence—that if all agencies had the unobserved characteristics of the New York City Police Department the total number of lethal encounters would be in the interval [161,298], compared with the observed 548; and if all agencies had Phoenix's unobservable attributes, the range for the total would be [850,1445]. The uncertainty here comes from the fact that the model's parameters required to construct the counterfactuals are estimated from the panel of deadly force incidents.

The Phoenix Police Department was associated with 93 deadly force incidents over the six year period. We find that they would have been responsible for only [11,32] killings if they had the unobserved covariates of the New York City Police Department. Conversely, the New York City Police Department (serving a much larger population) had 55 lethal encounters over the same period, but would have been responsible for [162,499] if they had the unobserved covariates of Phoenix Police Department.

We also estimate the effects of changes in observed characteristics. These can be obtained directly from the coefficients of the Poisson regression model, treating the unobserved variables as fixed effects. The sign on officers per population is positive, statistically insignificant, and relatively small in magnitude: reducing the size of a police force by one officer per thousand population leads to a reduction in lethal encounters of 1.2%.[6] Reducing gun

[5]These numbers are based on killings that involved on-duty officers from a single police department; the precise criteria for assignment of homicides to agencies is described below. The remaining deadly force incidents were associated with sheriff's offices, state and federal agencies, highway patrols, and other non-local agencies that do not have a well-defined or meaningful population served.

[6]This does not necessarily imply that contraction in department size would result in fewer police killings at the margin; the overall effect would also depend on the impact on overall homicide victimization, which has been found to be negatively correlated with force size (Chalfin et al., 2021).

death rates (unrelated to police action) by one percentage point reduces lethal encounters by about 4.9%, while reducing the poverty rate by one percentage point leads to about 4% fewer lethal encounters in a given year. In Section 5, we consider the question of whether these effects are policy relevant and economically meaningful.

Finally, we consider counterfactuals where we change both unobserved covariates and observed covariates. Our results suggest that the observed characteristics of some agencies—along with their unobserved covariates—offer a path towards a significant reduction in lethal encounters. Specifically, if all agencies had the observed and unobserved characteristics of the New York City Police Department the lethal encounters would be reduced from 548 to be in [115,189]. This is a reduction of at least 359 lethal encounters over a six year period.

The rest of this paper is organized as follows. Section 2 presents the model. Section 3 defines agency-specific counterfactuals and formalizes an Empirical Bayes strategy to estimate them. Section 4 describes our constructed data set. Section 5 presents results and Section 6 discusses extensions. All proofs are collected in the Appendix.

2 Model

This section presents the econometric framework that will be used to define the counterfactual objects of interest. The methods developed in this section combine Poisson Regression models for count panel data (Hausman, Hall and Griliches, 1984), counterfactual analysis in econometric models (Blinder, 1973; Oaxaca, 1973; Stock, 1989; Dinardo, Fortin and Lemieux, 1996; Chernozhukov, Fernández-Val and Melly, 2013), and Empirical Bayes methods (Robbins, 1956, 1964; Efron, 2010).

2.1 Notation

An integer-valued outcome variable, Y_{jt}, is observed for $j = 1 \dots J$ different units during $t = 1 \dots T$ periods.[7] The panel is short (in that $T << J$). We collect the j-th unit outcome variables in the vector $\mathbf{Y}_j \equiv (Y_{j1}, \dots, Y_{jT})^\top$. We use $\bar{Y}_j$ to denote the sum $\sum_{t=1}^{T} Y_{jt}$ across all periods for unit j.

For each unit we observe K *time-varying* covariates ($X_{jt} \in \mathbb{R}^K$) and L *time-invariant* covariates ($Z_j \in \mathbb{R}^L$). We assume there is also a vector of M *unobserved* time-invariant covariates ($W_j \in \mathbb{R}^M$).

We stack the time-invariant covariates in the column vector $\mathbf{X}_j \equiv (X_{j1}^\top, \dots, X_{jT}^\top)^\top$. Thus, $\mathbf{X}_j$ collects all the covariates of unit j over the different time periods $t = 1, \dots, T$. We sometimes use $\mathbf{X}_{jk}$ to denote the time series of covariate k for unit j. For simplicity of notation, we assume that all covariates have a discrete distribution. Sometimes we write $(W_j, \mathbf{X}_j, \mathbf{Y}_j, Z_j)$ to denote the vector that contains observed and unobserved variables, even though the dimensions do not match. We also do this for other vectors whenever it simplifies notation.

2.2 Assumptions

Assumption 1: The random vector $(W_j, \mathbf{X}_j, \mathbf{Y}_j, Z_j)$ is i.i.d. across units. In addition,

$$\mathbb{P}(Y_{jt}|W_j, \mathbf{X}_j, Z_j) \sim \text{Poisson}(\alpha_j \lambda_{jt}), \quad \lambda_{jt} \equiv \exp(X_{jt}^\top \beta + Z_j^\top \gamma), \quad \alpha_j \equiv \exp\left(W_j^\top \delta\right), \tag{1}$$

and $(Y_{j1}, \dots, Y_{jT})$ are i.i.d. across time, conditional on $(W_j, \mathbf{X}_j, Z_j)$.

Assumption 1 readily implies

$$\mathbb{E}[Y_{jt}|W_j, \mathbf{X}_j, Z_j] = \alpha_j \exp(X_{jt}^\top \beta + Z_j^\top \gamma). \tag{2}$$

[7] See Cameron and Trivedi (2015, Chapter 8) for a review of models for count panel data.

Thus, the unobserved characteristics simply change the scale of the conditional mean. A key assumption is that after conditioning on the unobserved characteristics, only the regressors at time t—and the time-invariant regressors—affect the conditional mean in that period. This can be interpreted as a typical strict exogeneity assumption. Assumption 1 also implies that the covariates of each unit are i.i.d. draws from some distribution, but the formulation allows for the covariates of each unit to be correlated over time. We assume $\alpha_j > 0$ for every j. This is a normalization.

It is well known that a short count panel enables consistent estimation of β as the cross-sectional observations grow large, without restricting the joint distribution of $(W_j, \mathbf{X}_j, Z_j)$.[8] It is also well-known that the estimation of γ requires additional "random-effects" type assumptions (Honoré and Kesina, 2017). We work under the following assumption:

Assumption 2: $\mathbb{E}[\alpha_j|Z_j]$ is strictly positive and does not depend on Z_j.

The estimation of the parameters β and γ in the model (1) under Assumptions 1 and 2 is described in Honoré and Kesina (2017).[9] We provide further details in Appendix B and implement the estimators using our own suite of Matlab functions.

3 Agency-specific counterfactuals

In this section we define the counterfactuals of interest. Our goal is to estimate the expected outcome of unit j at time t, but replacing the unobserved characteristics of unit j by those of unit j'. With the application to police use of lethal force in mind, we will refer to units as agencies and periods as years.

[8]See, for instance, Cameron and Trivedi (2015) Section 8.3.4.

[9]Honoré and Kesina (2017) compare their estimators of β and γ to a correlated random effects (CRE) estimator which includes the average of the time-varying explanatory variables as covariates in a random effects Poisson estimator (assuming the random effects have a Gamma distribution). Their simulations suggest that that the CRE estimator is biased for the coefficients of the time-varying variables, and the bias does not change much with the sample size.

Definition: Let x_t be a vector of K time-varying covariates. Let z be vector of L time-invariant covariates. Given vectors of observed characteristics $x \equiv (x_1^\top, \ldots, x_T^\top)^\top$ and z, the (x, z, j')-counterfactual of agency j at time t is defined as

$$\theta_t(j; x, z, j') \equiv \mathbb{E}[Y_{jt} | W_{j'}, x_1, \ldots, x_T, z] = \alpha_{j'} \exp(z'\gamma + x_t^\top \beta), \quad \text{where } \alpha_{j'} \equiv \exp\left(\delta^\top W_{j'}\right). \tag{3}$$

In the context of our empirical application, this is the expected number of homicides for agency j, provided that this agency has the observed covariates (x, z) and the unobserved characteristics of agency j'.

Consistent estimation of (3) is challenging. The short panel means there is limited time-series variation to estimate the effect of unobserved characteristics on the conditional mean. Thus, instead of insisting on consistent estimation of (3) we will focus on obtaining its best estimator, $\widehat{\theta}_t^*(j; x, z, j')$, under squared-loss minimization

$$(\widehat{\theta}_t^*(j; x, z, j') - \theta_t(j; x, z.j'))^2.$$

Let D denote the data available from all units (outcome variables, time-varying covariates and time-invarying covariates). As usual, we define an estimator $\widehat{\theta}_t(j, x, z, j')$ for $\theta_t(j, x, j')$ as a mapping from the data D at hand to the real line.

We would like to evaluate the performance of the estimator $\widehat{\theta}_t(j, x, j')$ in *repeated samples*; this means that we take new draws from the data, jointly with the unobserved characteristics of agency j', and for each new draw compute the squared distance

$$\left(\widehat{\theta}_t(j; x, z, j') - \theta_t(j; x, z, j')\right)^2$$

for fixed values of x and z. We then integrate over the joint distribution of $(D, \alpha_{j'})$.[10]

The following result is a generalization of the results of Robbins (1956) for Poisson Regression, to the set-up of a Poisson model for count panel data.

Proposition: Suppose the joint distribution of $(W_j, \mathbf{X}_j, Z_j)$ and the parameters (β, γ) are known. Under Assumption 1, the best estimator of $\theta_t(j; x, z, j')$ under squared-loss is

$$\widehat{\theta}_t^*(j; x, z, j') \quad = \quad \mathbb{E}[\alpha_{j'}|\mathbf{X}_{j'}, \mathbf{Y}_{j'}, Z_{j'}] \cdot \exp\left(x_t^\top \beta + \gamma^\top z\right). \tag{6}$$

Moreover,

$$\mathbb{E}[\alpha_{j'}|\mathbf{X}_{j'}, \mathbf{Y}_{j'}, Z_{j'}] = \frac{\overline{Y}_{j'} + 1}{\exp(\gamma^\top Z_{j'}) \sum_{t=1}^{T} \exp(X_{j't}^\top \beta)} \cdot \frac{\mathbb{P}(\overline{Y}_{j'} + 1|\mathbf{X}_{j'}, Z_{j'})}{\mathbb{P}(\overline{Y}_{j'}|\mathbf{X}_{j'}, Z_{j'})}, \tag{7}$$

where $\overline{Y}_j = \sum_{t=1}^{T} Y_{jt}$ represents the total counts associated to unit j in the time series.

Proof: See Appendix. □

The proof of the proposition above has two parts. The first part is a straightforward application of the decision-theoretic optimality of the posterior mean under quadratic loss. When (β, γ) are known and (x, z) are fixed, the counterfactual of interest is proportional to $\alpha_{j'}$. If we view $\alpha_{j'}$ as a random variable, its best estimator under quadratic loss is the posterior mean of $\alpha_{j'}$ given the data. The independence assumption implies that the only

[10] We do this by averaging first over the distribution of D—conditional on $\alpha_{j'}$—and then over the marginal distribution of $\alpha_{j'}$. In light of Assumption 1, we can write the joint distribution of D conditional on $\alpha_{j'}$ as

$$\mathbb{P}(\mathbf{X}_{j'}, \mathbf{Y}_{j'}, Z_j|\alpha_{j'}) \cdot \mathbb{P}(D_{-j'}), \tag{4}$$

where $D_{-j'}$ denotes all the data except for the the homicides and covariates of agency j'. Thus, algebra shows that the average squared error can be written as

$$\int \left(\sum_{(\mathbf{X}_{j'}, \mathbf{Y}_{j'}, Z_{j'}, D_{-j})} \left(\widehat{\theta}_t(j, x, z, j') - \theta_t(j, x, z, j')\right)^2 \mathbb{P}(\mathbf{X}_{j'}, \mathbf{Y}_{j'}, Z_{j'}|\alpha_{j'}) \mathbb{P}(D_{-j'}) \right) d\mathbb{P}(\alpha_{j'}) \tag{5}$$

relevant part of the data are the outcomes and covariates of unit j'.

The second part of the result follows Robbins (1956) and expresses the posterior mean of the unobserved unit-specific effects in terms of the marginal distribution of outcomes and covariates. The Empirical Bayes version of (6) replaces unknown quantities—β's, γ's and $\mathbb{P}(\bar{Y}_j|\mathbf{X}_j, Z_j)$—by plug-in estimators.

Our approach makes no parametric assumptions about the joint distribution of observable and unobservable characteristics. This is possible because we have postulated a parametric model for the conditional distribution of outcomes given observables and unobservables.

The panel data version of Robbins' formula in Equation (6) requires plug-in estimators of the ratio $\mathbb{P}(\overline{Y}_j + 1|\mathbf{X}_j, Z_j)/\mathbb{P}(\overline{Y}_j|\mathbf{X}_j, Z_j)$. In Robbins (1956)'s original cross-sectional formulation of the problem, the ratio is estimated by relative frequency counts. It is well-known that the classical solution performs poorly without "smoothing" (Brown, Greenshtein and Ritov, 2013).[11] One alternative is to estimate these conditional probabilities using Bayesian semiparametric methods, which we leave for future work.[12]

We will argue that in the empirical application we consider, it will make sense to assume $\mathbb{P}(\overline{Y}_j + 1|\mathbf{X}_j, Z_j)/\mathbb{P}(\overline{Y}_j|\mathbf{X}_j, Z_j) = 1$, provided we focus on counterfactuals involving large police departments (such as the New York City Police Department). In the case of the New York City Police Department, the implicit assumption will then be that the probability of observing 55 lethal encounters over 2013-2018—conditional on observed covariates—is the same as observing 56. We report counterfactuals for the ten largest departments (in terms

[11] One of the proposals in Brown, Greenshtein and Ritov (2013) is to assume that the observed outcomes have a Poisson measurement error. This leads to a formula similar to that derived by Robbins but using a smoothed estimator for the marginal probabilities. It would be interesting to adjust their suggested estimators to this context, perhaps by estimating each "cell" defined by the values of $\mathbf{X}_j$ separately. An important challenge in implementing this approach is that cells obtained by conditioning on the covariates may contain very few observations (just think of how many LEAs have the same covariates as the New York Police Department).

[12] For example, Carota and Parmigiani (2002) have proposed a Bayesian semiparametric model for regression problems in which the outcome variable is a count. Their approach is relevant for data sets in which the total number of occurrences in each cell defined by the values of $\mathbf{X}_j$ is of moderate size. Broadly speaking, the idea is to model the cumulative distribution of $Y_j|X_j$ as a Dirichlet Process Mixture. The Dirichlet Process is characterized by a "mean" conditional distribution and a scalar "dispersion" parameter. Both the mean conditional distribution and the scalar dispersion parameters are specified as being a parametric function of the covariates.

of population served) under this assumption.

3.1 Confidence Intervals for Estimated Counterfactuals

How do we quantify the uncertainty in the counterfactual parameter, $\widehat{\theta}_t^*(j; x, j')$, suggested in this paper? Our estimated counterfactual is

$$\widehat{\theta}_t^*(j; \mathbf{X}_j, j') \quad = \quad \frac{\overline{Y}_{j'} + 1}{\exp(Z_{j'}^\top \widehat{\gamma}) \sum_{t=1}^T \exp(X_{j't}^\top \widehat{\beta})} \cdot \frac{\widehat{\mathbb{P}}(\overline{Y}_{j'} + 1 | \mathbf{X}_{j'}, Z_{j'})}{\widehat{\mathbb{P}}(\overline{Y}_{j'} | \mathbf{X}_{j'}, Z_{j'})} \cdot \exp\left(X_{jt}^\top \widehat{\beta} + Z_j^\top \widehat{\gamma}\right).$$

The uncertainty in this counterfactual comes from the fact that we are using the data to replace population parameters (β, γ, and $\mathbb{P}(\bar{Y}_j | \mathbf{X}_j)$) by their sample counterparts ($\widehat{\beta}$, $\widehat{\gamma}$, $\widehat{\mathbb{P}}(\bar{Y}_j | \mathbf{X}_j)$). Thus, we can account for the uncertainty in the estimated counterfactual by delta-method/bootstrap arguments, provided we treat the remaining aspects of the counterfactual (such as $X_{jt}, \bar{Y}_j$ and Z_j) as fixed. Though this idea is quite natural, the only similar approach we found in the literature is Ignatiadis and Wager (2019), who rely on projection methods rather than bootstrap/delta-method arguments.

To give a concrete idea of how the approach works in our case. Suppose that it is known that

$$\frac{\mathbb{P}(\overline{Y}_{j'} + 1 | \mathbf{X}_{j'})}{\mathbb{P}(\overline{Y}_{j'} | \mathbf{X}_{j'})} = 1.$$

Under this assumption, it is straightforward to quantify the uncertainty in the estimation of $\widehat{\theta}_t^*(j; x, j')$. To do this, we first estimate $\widehat{\beta}$ and $\widehat{\gamma}$ by excluding observations j and j'. Because all the units are independent, excluding j and j' guarantees that one can condition on $(\mathbf{Y}_{j'}, \mathbf{X}_{j'}, \mathbf{Y}_j, \mathbf{X}_j)$ without having to take into account possible changes on the distribution of the estimated parameters. The counterfactual can then be viewed—conditional on $(\mathbf{Y}_{j'}, \mathbf{X}_{j'}, \mathbf{Y}_j, \mathbf{X}_j)$—as a differentiable function of β and γ. We can approximate the distribution

$$\widehat{\theta}_t^*(j; x, j') | (\mathbf{Y}_{j'}, \mathbf{X}_{j'}, \mathbf{Y}_j, \mathbf{X}_j).$$

using the delta method or resampling procedures like the bootstrap. In the paper we consider two such approaches. The first one, samples directly from the estimated asymptotic distribution of $\widehat{\beta}$ and $\widehat{\gamma}$. The second one is a conventional nonparametric bootstrap that samples from the empirical distribution of $(\mathbf{X}_j, Y_j, Z_j)$ (excluding the agencies j and j'). The tables reported in the main body of the paper use the former approach, and in the appendix we report the latter.

Alternative Approaches to Quantify Uncertainty: The counterfactual parameter of interest is a function of the agency-specific effect, α. It is then possible to construct Empirical Bayes confidence intervals for α under parametric assumptions on the conditional distribution of $\alpha_j|\mathbf{X}_j$—which we want to avoid— see Carlin and Louis (2000), Chapter 3.5.2. The construction of confidence intervals without strong parametric assumptions on the distribution of the unobserved effects is a more delicate matter. Recently, Armstrong, Kolesár and Plagborg-Møller (2020) suggest a robust Empirical Bayes confidence interval for unobserved effects in the Gaussian means problem. Koenker (2020) approaches the same problem using the non-parametric methods of Kiefer and Wolfowitz (1956) and Efron et al. (2019). It would be interesting to adapt these procedures to the construction of Empirical Bayes confidence intervals for counterfactual parameters.

4 Data

We have constructed a comprehensive agency-level data set to compute counterfactuals for police homicides. These data include a large number of law enforcement agencies (not only those that have been associated with police homicides), along with several agency and population attributes. The data set is constructed in a series of steps as follows.

Our source for the homicide data is *Mapping Police Violence* (MPV), which is a list of victims of lethal force along with the agency responsible (if known).[13] We use MPV rather

[13]There are three other widely used and publicly available data sources on police homicides: the Guardian's *Counted* Project covering 2015-16, the Washington Post's Fatal Force project dating back to 2015 for firearm

than other listings of police homicides, because this data includes the Originating Agency Identifier (ORI) code for the agency (or agencies) involved in each incident. This is a nine-character identifier assigned to each agency that has met established qualifying criteria for a fingerprint based background check, and can be used to easily match incidents with agencies in several standard official data sets.[14]

For the period 2013-2018, there are a total of 6,547 victims across all incidents. Of these a total of 5,885 homicides arise from an on-duty encounter involving intentional use of deadly force and a single, identified agency. We restrict attention to this subset of lethal encounters, but refine it further by imposing two additional requirements. First, the agency involved must have a known ORI code. Second, we require that the agency serve a well-defined population in the last available wave of the Law Enforcement Agency Identifiers Crosswalk (LEAIC). This excludes incidents involving federal organizations such as the FBI or DEA, as well as state troopers, highway patrols, transit police, and several other non-local agencies.[15] We also exclude sheriff's offices, even though some of these are large and are associated with defined local populations, since the nature of their functions varies quite considerably.

After matching, we have 13,397 police departments responsible for 3,877 homicides, and our analysis focuses exclusively on these.[16] The addition of covariates further reduces cov-

deaths (Finch et al., 2019), and *Fatal Encounters*. Edwards, Lee and Esposito (2019) have recently used the Fatal Encounters data to estimate the risks faced by different social groups of being killed by police in the United States and Schwartz and Jahn (2020) have used it to describe the distribution of police homicides across metropolitan areas.

[14]In a few cases the ORI code listed in the database matches to agencies with zero officers or population served, and needs to be substituted—this is the case for the primary police departments serving Jacksonville and Indianapolis for example. There is also some controversy about coverage and classification in the MPV data; see Nix and Lozada (2021) for a critique and Bor et al. (2020) for a reply. This controversy does not pertain to our analysis. It concerns 93 incidents, allegedly misclassified with respect to weapon possession by victims, or the presence of mental health crises, neither of which are variables that we use. In addition, a number of these incidents are excluded from our analysis because they do not meet our criteria of involving deliberate use of force by on-duty officers.

[15]Many of these agencies are tied to police homicides, some of them within the jurisdictions that agencies in our data set have primary responsibility for.

[16]There are more than 28,000 complete agencies in the LEAIC data, but these include many special jurisdictions that do not serve well-defined populations, such as those associated with parks and recreation, transportation systems, and public buildings and facilities. We focus only on local police departments, which are easily associated with well-defined and mutually exclusive populations. Local police departments account for only around 62% of police homicides, and many of the homicides associated with other agencies occur within the jurisdictions of local police departments. Moreover, local police departments sometimes kill

erage as we describe next.

4.1 Additional Covariates

In order to obtain further covariates we use two data sets that are part of the Uniform Crime Reporting (UCR) program—the Law Enforcement Officers Killed and Assaulted (UCR-LEOKA) database, and the the Offenses Known to Law Enforcement (UCR-OKLE) database.[17] In addition, we draw on the 2018 American Community Survey (ACS) from the Census Bureau, and, finally, data on mortality by county from the Center for Disease Control and Prevention (CDC). We next describe which variables are extracted from each source, and also how many agencies we lose due to data unavailability.

Officers per 1,000 population served: This variable is obtained from the UCR-LEOKA database, after matching on ORI. We use the 2012 wave for consistency with the crosswalk data. For this year, we find information on the size of the force (number of sworn officers) and find this to be positive for 12,012 out of the 13,397 police departments.[18] These departments account for 3,856 out of the 3,877 homicides.[19]

Murders per 100,000 population served: This variable is obtained from UCR-OKLE and uses the total murders (and non-negligent manslaughters) reported by the agency, annually for 2013-2018. We include only those police departments with complete reports for all months in the period considered, and use the time-varying values of the population served, also extracted from the UCR-OKLE data. This leaves us with 7,732 agencies, accounting for 3,542 homicides.

civilians outside their jurisdictions–for instance as the culmination of a high-speed chase.

[17]Our sources for the UCR data are the concatenated files constructed by Kaplan (2021*a*,*b*).

[18]As Chalfin and McCrary (2018) point out, even within a single year, the number of officers in a police department cannot be measured without error. Large departments especially do not time new hires to match exactly with retirements, resignations, and other departures. Even within the set of people on the payroll at any moment, some are usually unavailable for service because they are on terminal leave, or in the training academy, or on vacation or personal leave, for instance. Departments also differ in the number of annual hours officers are expected to work.

[19]This data set also includes counts of officers killed (by felony or accident) and assaulted (with and without injury). In the Appendix we add officers assaulted to our main specification and show that our results barely change.

Poverty, demographics, and land area: We add the share of the population living in poverty, and the share of the population that identifies as (non-Hispanic) Black using data from the 2018 five-year ACS. This is challenging because police departments do not correspond exactly to census geographies in a consistent way. We adopt a sequential procedure using data on census places, county subdivisions, and counties as follows. We first see if an agency matches a census place, and assign that data to the agency if it does. If it corresponds to no census place, we check whether it matches a county subdivision, and assign data accordingly if it does. For agencies still unmatched, we see whether they are county departments. If so, the county data are assigned to the agency, after subtracting the data that has already been assigned to other agencies in the same county.

A similar procedure is used to assign land area (measured in square km) to agencies, based on 2018 ACS data. Here we sum all land areas corresponding to the census place associated with each agency. If the agency does not correspond to a census place, we repeat the procedure using county subdivision rather than place. This leaves the county agencies, and for these we assign county land areas, after first subtracting the total land area already assigned to other agencies in the same county.

Most agencies are successfully matched with census data in this way. We are left with 7,667 police departments that account for 3,534 homicides.

Garner and LEOBR dummies: Under the current federal civil standard, established in the 1985 *Tennessee v. Garner* case, "a police officer may use deadly force to prevent the escape of a fleeing suspect only if the officer has a good-faith belief that the suspect poses a significant threat of death or serious physical injury to the officer or others." That is, an officer cannot simply shoot a fleeing suspect who poses no immediate danger. Some states have adopted this standard as part of criminal law (or had already done so prior to the federal ruling), while others continue to operate under a more permissive common law standard that gives police greater latitude in using deadly force. Flanders and Welling (2015) provide a classification of states into those that have adopted *Garner* or *Garner*-like principles in criminal matters and those that have not done so. We use this to create a dummy variable assigned to each agency, based on the state in which it is located.[20] Finally, to capture the power of police unions in protecting officers from allegations of misconduct, we use Rushin (2016) to assign to each agency a variable indicating whether it is in a jurisdiction with a Law Enforcement Officer Bill of Rights (LEOBR).[21]

Gun Death Rate: Using the CDC data on mortality by county, we attach to each agency the number of gun deaths per 100,000 population in the county in which it is located. We include all deaths (including suicides) resulting from firearm discharges, except for those attributed to law enforcement actions (since this is our dependent variable). This variable is a measure of gun prevalence at the county level. We use all deaths from 1999-2016. For privacy reasons, the CDC suppresses data for counties with ten or fewer gun deaths over this period, and we drop all agencies in such counties.

This gives 7,609 police departments, accounting for a total of 3,533 homicides. In estimating the model, we restrict attention to agencies in the continental United States, excluding 22 agencies in Alaska and 2 in Hawaii, collectively responsible for 29 homicides. These states are unusual in several respects, particularly in the vast amounts of land area covered by their agencies. Of the five agencies in our data with the largest land area, four are in Alaska and one in Hawaii. The very largest—Alaska's North Slope Borough Police Department—covers almost 230,000 square kilometers, an order of magnitude greater than the 10,000 square kilometers covered by the second largest, Hawaii County Police Department. Much of this is unpopulated public land, and including these agencies would distort any estimates involving population density. Thus, the final data set used for estimation consists of 7,585 police departments that account for 3,504 homicides from 2013 to 2018.

[20] The status of Montana is listed as unclear in Flanders and Welling (2015) and we pool this with the non-Garner states.

[21] This is a state level dummy, with the exception of Texas, which has a bill of rights applicable only to agencies in cities with more than 1.5 million people. In our data this applies only to the Houston Police Department.

5 Results

5.1 Estimation of β and γ

We start by estimating the parameters (β, γ) in model (1):

$$\mathbb{P}(Y_{jt}|W_j, \mathbf{X}_j, Z_j) \sim \text{Poisson}(\alpha_j \lambda_{jt}), \quad \lambda_{jt} \equiv \exp(X_{jt}^\top \beta + Z_j^\top \gamma), \quad \alpha_j \equiv \exp\left(W_j^\top \delta\right),$$

where we further assume $(Y_{j1}, \ldots, Y_{jT})$ are i.i.d. across time, conditional on $(W_j, \mathbf{X}_j, Z_j)$.

Our only time-varying variable (X_{jt}) is murders per 100,000 population. Our time-invariant variables (Z_j) are as follows: the natural logarithm of population (in millions); officers per 1,000 population; the gun death rate; the proportion of population with income below the poverty level; proportion of population who are (non-Hispanic) Black; and land area (in square kilometers) per million population. We also include Garner and LEOBR dummies. See Section 4 for details on how these variables are constructed.

Since we are interested in counterfactuals involving the 10 largest police departments in terms of population served, we leave them out in our estimation procedure. This procedure is described below.

Estimation of β: The standard procedure for estimating β in model (1) uses the sample moment conditions:

$$\frac{1}{J}\sum_{j=1}^{J}\left(\frac{1}{T}\sum_{t=1}^{T} X_{jt}\left(Y_{jt} - \frac{\exp(X_{jt}^\top\beta)}{\sum_{t=1}^{T}\exp\left(X_{jt}^\top\beta\right)}\bar{Y}_j\right)\right) = \mathbf{0}, \tag{8}$$

which can be motivated as a Generalized Method of Moments estimator using the mean in (2) or as a conditional (quasi)-Maximum Likelihood estimator obtained from the Poisson likelihood.[22]

[22]See Section 8.3.4 in Cameron and Trivedi (2015) and Section 18.7.4 in Wooldridge (2010). Equation (1) implies:

$$(Y_{j1}, \ldots, Y_{jT})'|\alpha_j, \mathbf{X}_j, Z_j, \bar{Y}_j \sim \text{Multinomial}\left(\bar{Y}_j, \left[\frac{\lambda_{j1}}{\sum_{t=1}^{T}\lambda_{jt}}, \ldots, \frac{\lambda_{jT}}{\sum_{t=1}^{T}\lambda_{jt}}\right]\right).$$

Writing the negative log-likelihood of the multinomial and taking derivatives with respect to β gives (8).

There are two important remarks about Equation (8). First, these moment conditions do not depend on γ. Second, the estimation of β only depends on the units for which $Y_{jt} > 0$ for some t. In the context of our example, this means that only the 1179 agencies with some lethal encounter over 2013-2018 are used to estimate the slope coefficients of time-varying parameters.

Estimation of γ: We follow Honoré and Kesina (2017) and exploit Assumption 2. The idea is that if β were known, the law of iterated expectations would imply

$$\mathbb{E}\left[\frac{\bar{Y}_j}{\sum_{t=1}^{T}\exp\left(X_{jt}^{\top}\beta\right)}\,\middle|\, Z_j\right] = \mathbb{E}[\alpha_j|Z_j]\exp\left(Z_j^{\top}\gamma\right). \tag{9}$$

Since $\mathbb{E}[\alpha_j|Z_j]$ is assumed to be independent of Z_j (and different from zero), equation (9) defines a nonlinear least-squares estimation problem where we can use the moment conditions

$$\frac{1}{J}\sum_{j=1}^{J}\left(\frac{\bar{Y}_j}{\sum_{t=1}^{T}\exp\left(X_{jt}^{\top}\beta\right)} - \exp(\gamma_0 + Z_j^{\top}\gamma)\right)\exp(\gamma_0 + Z_j^{\top}\gamma)[1, Z_j']' = \mathbf{0}. \tag{10}$$

The full estimation routine then proceeds as follows:

1. Equation (8) is used to estimate β. Denote the resulting estimator $\widehat{\beta}$.
2. Plug-in $\widehat{\beta}$ in Equation (10), and use the resulting moment condition to estimate γ. Denote the resulting estimator as $\widehat{\gamma}$.

The estimators can be viewed as GMM estimators using the moment conditions (8) and (10). Standard errors can be obtained analytically following the formulae in Section 6.3 of Newey and McFadden (1994). We compute the estimators and their standard errors using our own suite of Matlab functions, provided in the GitHub repository with replication materials.[23]

Table 1 presents the estimated values of (β, γ), with standard errors clustered by agency.

[23] https://github.com/jm4474/EmpiricalBayesCounterfactuals

Table 1: Coefficient Estimates

	Coefficient	Standard Errors
Murder per pop. (in hundred thousands)	0.005	0.008
Log of Avg. pop. (in millions)	1.192	0.104
Officers per pop. (in thousands)	0.012	0.01
Gun Death Rate (%)	0.049	0.017
Share in Poverty (%)	0.04	0.014
Share Black (%)	-0.024	0.008
Garner	-0.031	0.242
LEOBR	-0.05	0.217
Land Area (sq. km.) per pop. (in millions)	1.0231e-05	1.9313e-06

The coefficient on log-population is slightly above one. This means that the conditional mean of lethal encounters scales almost multiplicatively in this variable.

The coefficient on officers per population is positive, but is not statistically different from zero at the 90%-level. Moreover, its magnitude is relatively small. To illustrate this point, consider the recent proposal to reduce the size of the New York City Police department by approximately 2,000 officers (Koeza and Lu, 2020). Such a reduction would decrease the officer per population ratio to about 4, from its current value of 4.16. The estimated effect of this change would be a reduction in lethal encounters of approximately $(0.012) \times 100 \times 0.16 \approx 0.19\%$. For the New York City Police Department this is a reduction of $55 \times 0.19\% \approx 0.1$ in lethal encounters over 2013-2018, or one lethal encounter every 60 years.[24]

The magnitude of the coefficient on the gun death rate is interesting. Reducing the gun death rate by one percentage point reduces lethal encounters by about 4.9%. This number is actually quite large, given recent findings in the literature suggesting that required background checks on handgun purchases from licensed firearm dealers—accompanied by a 2–7 days waiting period to allow sufficient time for the check—can reduce gun homicides

[24]Changes in the size of a police department have qualitative as well as quantitative implications. Certain tasks, such as responding to calls associated with homelessness, mental health issues, nuisance complaints, or conflict in schools can be shifted to other agencies, thus altering the nature of police-civilian contact. Behavioral changes among officers and the population they are expected to serve are also likely to follow on the heels of a contraction. A statistical model such as that we have constructed here is ill-equipped to examine the consequences of such qualitative changes. Nevertheless, our framework allows us to conduct a counterfactual analysis of limited scope.

by 17% (Luca, Malhotra and Poliquin, 2017). Our gun death covariate includes all deaths (including suicides) resulting from firearm discharges, and we estimate that only 37% of firearm deaths are homicides. Thus, the suggested changes on background checks could reduce lethal encounters by about 31%.

Regarding the demographic variables, there are two important remarks. First, the poverty rate fell by 2.3 percentage points between January-February 2020 and April-May 2020 (from 10.9% to 8.6%), and Han, Meyer and Sullivan (2020) estimate that the government programs expanded or enacted at this time can more than account for the full drop that occurred. Our estimates suggest that this reduction in poverty could translate into a reduction of lethal encounters of around 9%.[25] Similarly, a study by the Center on Budget and Policy Priorities (Trisi and Saenz, 2019) suggests that the poverty rate in the United States has fallen from 26.0 percent in 1967 to 14.4 percent in 2017, "largely due to the growing effectiveness of economic security programs such as Social Security, food assistance, and tax credits for working families." If we assume the rate of reduction in poverty was constant over the years (although, most likely, most of the reduction occurred before 1975), the annualized rate of poverty reduction attributed to economic security programs is about 1.17%. According to our estimates, such a reduction in poverty is associated with approximately 4.68% fewer lethal encounters in a given year. The average yearly number of lethal encounters in our data is $3,533/6 \approx 589$. Thus, feasible reductions in the poverty rate translate into about 28 fewer lethal encounters per year in the limited set of agencies that we consider. All this suggests that government programs, through their effects on poverty, can contribute to a meaningful reduction in the incidence of deadly force.

Second, the coefficient on the Black population share is negative and significant at conventional levels. This result does not imply that Black civilians are less likely to be killed by police, either conditionally or unconditionally. Recall that the dependent variable is the

[25]This estimate could actually be conservative, given that the coronavirus relief package that Congress passed in December 2020 likely resulted in a 4.2 percentage point drop in the (Supplemental Poverty Measure) poverty rate in January 2021 (Parolin and Curran, 2021).

number of victims of all groups. Conditional on the other covariates (some of which like murder and poverty are positively correlated with the Black population share), jurisdictions with more Black residents have police departments that kill fewer civilians. This result is consistent with the observation that the states with the highest rates of police homicides per capita—New Mexico, Arizona, Oklahoma, Nevada, Colorado, and West Virginia in our data—have relatively small Black populations, with none of them above the median state on this dimension. Conversely, the states with the largest Black populations—Mississippi, Georgia, Louisiana, Maryland, and South Carolina—have rates of per capita police homicide well below those of the deadliest states.[26]

The relationship between population sparsity and police homicide is complex. On the one hand, dense populations of civilians are more likely to interact with one another and engage in disputes that escalate to a point where fatal police involvement occurs. We partially control for this effect by including the murder variable (murders are highly concentrated in urban areas). On the other hand, in sparsely populated communities police officers may be more likely to confront dangerous situations alone because backup is further away and because they might patrol without partners. Solitary police may fear for their safety more. Specialized services, whether within the police department or outside it (for instance, mental health professionals) may be further from the scene of the confrontation (or absent entirely because the sparsity keeps them from being effective). Hospitals are likely to be further away too, and so some shootings that would not be fatal in more densely populated communities may turn fatal in sparsely populated communities (realizing this for themselves may also induce police to be quicker to shoot).

All in all, our data indicate that the second effect is stronger on average: more killings occur in sparser places, *ceteris paribus*. While the coefficient is statistically significant, it is not economically significant. Moreover, the size and significance of the results are not

[26] See O'Flaherty and Sethi (2019) for a deeper discussion of the correlation between deadly force and population composition at the state level. We will examine racial disparities in police killings in a companion paper.

completely robust to changes in specification and to the treatment of Alaska.

5.2 Pairwise Agency Comparisons

For any pair of agencies j and j' we can ask the following counterfactual question: To what extent would agency j's lethal encounters have been different if it had unobserved agency-specific characteristics $\alpha_{j'}$ (instead of α_j), without any change in its own covariates $\mathbf{X}_j$? That is, what would be the consequence for the agency j lethal encounters of replacing agency j's unobserved characteristics with those of agency j', leaving all observed characteristics intact?

Table 2: Counterfactual police homicides for 2013-2018: Unobserved Covariates

	Phoenix	Las Vegas	Dallas	Philadelphia	San Diego	Chicago	Los Angeles	Houston	San Antonio	New York
Phoenix	**93**	[59,76]	[41,95]	[33,110]	[45,74]	[40,77]	[41,58]	[40,59]	[33,68]	[11,32]
Las Vegas	[64,83]	**51**	[34,70]	[27,81]	[37,54]	[33,57]	[30,48]	[32,44]	[26,53]	[8,25]
Dallas	[34,78]	[25,53]	**33**	[25,43]	[22,45]	[21,44]	[17,43]	[19,38]	[21,31]	[7,14]
Philadelphia	[25,82]	[19,56]	[23,40]	**28**	[17,45]	[18,40]	[13,43]	[15,37]	[15,36]	[6,13]
San Diego	[34,57]	[26,38]	[20,42]	[17,45]	**26**	[21,32]	[18,30]	[19,27]	[15,33]	[5,14]
Chicago	[78,150]	[58,100]	[49,106]	[46,103]	[54,82]	**63**	[41,78]	[48,64]	[36,85]	[13,35]
Los Angeles	[185,263]	[124,199]	[91,225]	[77,249]	[103,175]	[93,178]	**113**	[91,141]	[75,162]	[27,69]
Houston	[83,124]	[61,85]	[47,95]	[41,102]	[53,72]	[52,69]	[42,65]	**51**	[35,74]	[12,32]
San Antonio	[50,102]	[35,73]	[39,57]	[29,70]	[30,66]	[27,64]	[25,55]	[25,53]	**35**	[10,20]
New York	[162,499]	[119,358]	[133,278]	[120,283]	[109,282]	[103,276]	[93,233]	[92,234]	[100,210]	**55**
Totals	[850,1445]	[623,1021]	[559,963]	[478,1043]	[552,843]	[515,840]	[472,712]	[483,684]	[435,727]	[161,298]

Note: Diagonal entries are observed lethal encounters (totaling 548 encounters). Off-diagonal entries are 90% confidence intervals for counterfactual values of lethal encounters, obtained by replacing the posterior expectation of α_j for the agency in the row with that of the agency in the column, while assuming no change in observed covariates. Agencies are listed in decreasing order by their estimated value of α_j.

Table 2 provides an answer to the question about counterfactuals for the ten largest police departments by population served, ordered by the size of the estimated posterior mean of α_j, from largest to smallest. The diagonal elements in the table are the actual number of lethal encounters, summed over the period 2013-18, while the off diagonal elements are 90% confidence intervals for the counterfactuals. The confidence intervals are constructed as described in Section 3.1, using 1,000 samples from the estimated asymptotic distribution of $(\hat{\beta}, \hat{\gamma})$. Specifically, each row tells us the counterfactual number of lethal encounters that a given agency would have been responsible for if there were no change in its covariates, but if it had the unobserved characteristics of the agency identified in the column.

Phoenix and New York are on opposite ends of the table. So, for example, the Phoenix Police Department had 93 lethal encounters over the six year period, but we can say with 90% confidence that they would have been responsible for only [11,32] if they had the unobservables of the New York City Police Department. The uncertainty here comes from the fact that (β, γ) are estimated from the panel on lethal encounters. The last column of Table 2 suggests that giving the unobservables of the New York City Police Department to each of the ten largest agencies in the country could reduce lethal encounters in all of them.

In fact, if one adds together all of the diagonal elements, the sum is 548, which is the total number of lethal encounters for this set of departments over the six year period considered. The counterfactual lethal encounters for this sum are reported at the bottom of the table. If all agencies had the unobserved characteristics of the New York City Police Department, the lethal encounters would be in [161,298]. If all agencies had the Phoenix unobserved covariates instead, the range would be [850,1445]. These are substantial effects that suggest considerable scope for learning from the best practices (and avoiding the worst) of other agencies.

Table 3 below complements the results above by considering changes to some of the agencies' observed covariates. In particular, we consider changes in variables that we believe can be affected by reforms to policing: officers per thousand population, the gun death rate, the poverty share, the Garner statutes, and the presence or absence of LEOBR.

Phoenix and New York remain at opposite ends of the table. Interestingly, in 2018 the New York Times published the article *"How Phoenix Explains a Rise in Police Violence: It's the Civilians' Fault"* (Oppel, 2018). A few days later, the Phoenix Law Enforcement Association issued a statement citing facts that make law enforcement in Phoenix particularly challenging.[27] The statement described the city as "violent and out of control". The estimated values suggest that indeed the Phoenix Police Department has to enforce the law in a rather challenging environment. According to the first column of Table 3, replacing

[27] https://azplea.com/2018/12/chief-williams-and-plea-respond-to-nyt-hit-piece/

Table 3: Counterfactual police homicides for 2013-2018: Observed Covariates

	Phoenix	San Antonio	Las Vegas	Los Angeles	Houston	Dallas	San Diego	Chicago	Philadelphia	New York
Phoenix	**93**	[65,83]	[65,84]	[61,82]	[50,78]	[46,76]	[40,66]	[36,71]	[23,66]	[21,57]
San Antonio	[41,52]	**35**	[32,41]	[33,36]	[26,36]	[24,34]	[22,29]	[19,32]	[12,30]	[12,25]
Las Vegas	[58,75]	[46,59]	**51**	[43,58]	[38,53]	[34,51]	[29,44]	[27,46]	[17,44]	[16,38]
Los Angeles	[131,175]	[115,123]	[103,137]	**113**	[88,116]	[81,111]	[72,95]	[63,103]	[42,95]	[39,80]
Houston	[62,97]	[52,71]	[51,72]	[51,67]	**51**	[47,50]	[36,50]	[37,47]	[24,44]	[21,39]
Dallas	[42,69]	[35,51]	[35,51]	[35,48]	[35,37]	**33**	[25,35]	[26,32]	[17,30]	[15,27]
San Diego	[38,63]	[33,45]	[32,48]	[32,43]	[28,39]	[26,37]	**26**	[21,33]	[15,30]	[14,25]
Chicago	[85,169]	[72,124]	[72,123]	[71,115]	[71,91]	[69,83]	[53,81]	**63**	[41,63]	[36,56]
Philadelphia	[41,117]	[35,85]	[34,86]	[35,78]	[34,63]	[33,57]	[26,54]	[30,45]	**28**	[22,31]
New York	[92,249]	[81,175]	[76,183]	[80,162]	[74,136]	[72,124]	[62,108]	[64,100]	[53,75]	**55**
Totals	[697,1148]	[593,815]	[570,851]	[587,760]	[554,630]	[522,589]	[424,543]	[418,532]	[278,497]	[257,426]

Note: Diagonal entries are observed lethal encounters (totaling 548 encounters). Off-diagonal entries are 90% confidence intervals for counterfactual values of lethal encounters, obtained by replacing Officers per 1k population, Gun Death Rate, Share in Poverty, Garner, and LEOBR of the agency in the row with that of the agency in the column. Agencies are listed in decreasing order by the estimated effect of these covariates, so entries decline as one reads across rows.

key observed covariates of each agency by those of the Phoenix Police Department would increase lethal encounters in each of the agencies under consideration. However, the results do not suggest that the scale of deadly force in Phoenix can simply be attributed to the environment faced by officers. The first column in Table 2 suggest that unobserved covariates also play an important role in explaining the large numbers of lethal encounters associated with the Phoenix Police Department.[28]

We also note that while the Phoenix Police Department and the New York City Police Department have the same ranking in Tables 2 and 3, other departments do not. The San Antonio, Los Angeles, and Houston police departments seem to combine "favorable" unobservables with "unfavorable" observables, while the opposite is true for the Philadelphia and Dallas police departments.

To finalize this section Table 4 considers counterfactuals where we change both unobserved covariates and observed covariates (in particular, those considered in Table 3). This table suggests that the observed characteristics of some agencies—along with their unobserved covariates—offer a path towards a significant reduction in lethal encounters. Specifically, if all agencies had the observed and unobserved characteristics of the New York City

[28]Moreover, the environment faced by officers of the Phoenix Police Department might as well be endogenous to the operation and configuration of the agency.

Police Department the lethal encounters would be reduced from 548 to be in [115,189]. This is a reduction of at least 359 lethal encounters over a six year period.

Table 4: Counterfactual police homicides for 2013-2018: Unobserved and Observed

	Phoenix	Las Vegas	Dallas	San Antonio	Los Angeles	Houston	San Diego	Chicago	Philadelphia	New York
Phoenix	**93**	[52,53]	[28,55]	[26,53]	[31,44]	[30,35]	[29,34]	[25,35]	[18,36]	[4,11]
Las Vegas	[92,94]	**51**	[27,55]	[26,53]	[31,44]	[30,35]	[29,34]	[25,35]	[17,36]	[4,11]
Dallas	[58,115]	[32,64]	**33**	[30,34]	[22,47]	[20,40]	[19,39]	[17,38]	[20,24]	[4,9]
San Antonio	[64,130]	[36,73]	[36,40]	**35**	[25,52]	[22,45]	[22,43]	[19,43]	[21,28]	[5,9]
Los Angeles	[246,346]	[136,194]	[82,176]	[79,166]	**113**	[88,114]	[81,118]	[76,112]	[52,114]	[14,32]
Houston	[140,163]	[78,91]	[44,89]	[41,86]	[52,67]	**51**	[44,58]	[43,53]	[28,57]	[7,18]
San Diego	[75,87]	[42,49]	[24,48]	[22,45]	[26,38]	[24,32]	**26**	[20,33]	[15,32]	[4,10]
Chicago	[171,240]	[96,133]	[57,124]	[54,121]	[65,96]	[63,78]	[53,86]	**63**	[38,78]	[9,25]
Philadelphia	[76,155]	[42,87]	[41,50]	[37,49]	[29,64]	[26,53]	[25,53]	[24,49]	**28**	[5,12]
New York	[460,1241]	[255,695]	[219,451]	[217,418]	[201,442]	[163,413]	[154,413]	[142,395]	[140,299]	**55**
Totals	[1543,2558]	[860,1435]	[649,1045]	[626,968]	[647,940]	[548,864]	[512,873]	[471,825]	[412,683]	[115,189]

Note: Diagonal entries are observed lethal encounters (totaling 548 encounters). Off-diagonal entries are 90% confidence intervals for counterfactual values of lethal encounters, obtained by replacing Officers per 1k population, Gun Death Rate, Share in Poverty, Garner, LEOBR, and the posterior expectation of α_j of the agency in the row with that of the agency in the column. Agencies are listed in decreasing order by the estimated effect of these covariates, so entries decline as one reads across rows.

A natural question regarding the results above concerns the relative role of observed and unobserved covariates in accounting for the counterfactual lethal encounters. Conducting a variance decomposition in a nonlinear model, without making specific assumptions about the joint distribution of $(\alpha, \mathbf{X}_j, Z_j)$, is challenging. However, the counterfactuals in Table 2 and 3 can provide useful information in selected cases. For example, take the case of the Philadelphia Police Department with characteristics of the New York City Police Department. Table 2 shows that the lethal encounters by Philadelphia Police Department would decrease from 28 to be in [6,13] if the unobserved characteristics of the New York City Police Department were transferable. Table 3, however, shows that the effect of changes in the covariates we believe can be affected by reforms to policing is ambiguous and in the interval [20,29]. These numbers suggest that the effects associated with transferring unobserved characteristics—which we take to include selection practices, training, promotion standards, disciplinary procedures, and organizational culture—are plausibly more important in the comparison between Philadelphia and New York.

In general, the relative importance of observed and unobserved characteristics is not as easy to assess as in the example above. One particular way to illustrate this point concerns the total reduction in lethal encounters corresponding to the ten largest departments by population served. Transferring the unobserved covariates of the New York City Police Department leads to a reduction from 548 to [161,298]. The change in selected observed covariates leads to a reduction to [228,371]. These changes are not easily amenable to ranking. However, we think there is value in reporting the counterfactuals in Table 2 and 3.

6 Extensions

6.1 Counterfactuals in Binomial Regression

A common critique of the use of the Poisson distribution is the so-called *overdispersion* problem. In a nutshell, this problem arises because the Poisson distribution forces the mean and the variance of the outcome variable to be equal. The overdispersion problem typically motivates the use of different statistical models for count data, such as the negative binomial distribution.

In this section, we study the extent to which our Empirical Bayes counterfactuals can be constructed by using other parametric models for $\mathbf{Y}_j|\mathbf{X}_j, Z_j\alpha_j$; for example, a binomial distribution instead of a Poisson. To simplify our discussion we assume there are no time-invariant covariates. We also show that our model has no overdispersion problem. Thus, the extension to other "kernels" (using Robbins' language) discussed in this section intends to provide a better understanding of the role of the Poisson parametric assumption in this paper.

Overdispersion: Under Assumption 1

$$\mathbb{E}[Y_{jt}|\mathbf{X}_j, \alpha_j] = \alpha_j \exp\left(X_{jt}^{\intercal}\beta\right) = \mathbb{V}(Y_{jt}|\mathbf{X}_j, \alpha_j).$$

Algebra shows that integrating out the agency-specific unobserved effect we obtain

$$\mathbb{V}(Y_{jt}|\mathbf{X}_j) = \mathbb{E}[Y_j|\mathbf{X}_j] + \mathbb{V}(\alpha_j|\mathbf{X}_j)\exp\left(2X_{jt}^{\intercal}\beta\right), \tag{11}$$

which will be strictly larger than $\mathbb{E}[\mathbf{Y}_j|\mathbf{X}_j]$ as long as α_j does not have a degenerate distribution. This means that in our framework there is no overdispersion problem.

Extension to Binomial Regression: Let $X_{1,jt}$ denote the number of officers of agency j at time t. Suppose

$$Y_{jt}|\mathbf{X}_j, \alpha_j \sim \text{Binomial}(\alpha_j\lambda_{jt}, X_{1,jt}),\ \lambda_{jt} \equiv \frac{\exp(X_j^{\intercal}\beta)}{1+\exp(X_j^{\intercal}\beta)} \tag{12}$$

and that $(Y_{j1}, \ldots, Y_{jT})$ are i.i.d. across time, conditional on $(\mathbf{X}_j, \alpha_j)$. The model above treats the number of officers as the number of trials in a binomial regression model in which each officer has a probability of committing a homicide equal to $\alpha_j\lambda_{jt}$. We make two assumptions. First,

$$\beta_1 = 0. \tag{13}$$

This means that the number of officers at time t do not affect the probability that each individual agent commits a homicide. Second

$$(\mathbf{X}_1 \perp \alpha_j)|(\mathbf{X}_2, \ldots, \mathbf{X}_T). \tag{14}$$

This is an important restriction, as we require the size of the agency to be independent of the unobserved characteristics, given the observable covariates. If α_j captures how violent civilians are towards the officers of an agency, the assumption says that— conditional on the other covariates—the unobservable characteristic does not affect the size of agency.

Proposition: Suppose conditions (13)-(14) hold. Define the set $\widetilde{\mathcal{Y}}(\mathbf{Y}_j, \mathbf{X}_j)$ as all outcomes $\tilde{\mathbf{Y}}_j$ and covariate values $\tilde{\mathbf{X}}_j$ for which

1. $\sum_{t=1}^{T} \tilde{Y}_{jt} = \bar{\mathbf{Y}}_j + 1$,

2. $\tilde{X}_{j1} - \tilde{Y}_{j1} = X_{j1} - Y_{j1}$,

3. $\mathbb{P}(\tilde{\mathbf{X}}_1|\mathbf{X}_j) = \mathbb{P}(\mathbf{X}_1|\mathbf{X}_j)$.

Then,

$$\begin{aligned}\mathbb{E}[\alpha_j|\mathbf{Y}_j, \mathbf{X}_j] &= \frac{1}{|\widetilde{\mathcal{Y}}(\mathbf{Y}_j, \mathbf{X}_j)|} \\ &\sum_{\tilde{\mathbf{Y}}_j, \tilde{\mathbf{X}}_j \in \widetilde{\mathcal{Y}}(\mathbf{Y}_j, \mathbf{X}_j)} \left(\Pi_{t=1}^{T} \frac{X_{1,jt}! \lambda_{jt}^{Y_{jt}} \tilde{Y}_{jt}!}{\tilde{X}_{1,jt}! \lambda_{jt}^{\tilde{Y}_{jt}} Y_{jt}!} \right) \frac{\mathbb{P}(\tilde{\mathbf{Y}}_j, \tilde{\mathbf{X}}_{1j}, \mathbf{X}_{2j}, \ldots, \mathbf{X}_{kj})}{\mathbb{P}(\mathbf{Y}_j, \mathbf{X}_j)}.\end{aligned}$$

Proof: See Appendix A.1 $\square$

The formula above shows that the posterior mean of α can still be represented in terms of the marginal distributions of $(\mathbf{Y}_j, \mathbf{X}_j)$. Because the distribution of $Y_{jt}|\mathbf{X}_j, \alpha_j$ varies over time, it is more difficult to derive an analogoue of Robbins' formula for the binomial kernel; see Robbins (1956, eq. 37). However, it is still theoretically possible to use the marginal distribution of $(\mathbf{Y}_j, \mathbf{X}_j)$ to estimate the posterior mean.

7 Conclusion

As explained elegantly by Gu and Koenker (2017), Empirical Bayes methods provide a convenient, and principled, approach to deal with unobserved heterogeneity in panel data (such as that arising from omitted variables for each unit). In this paper we have proposed a simple framework that allows for the construction of unit-specific counterfactuals to changes in observed and unobserved characteristics.

The empirical application that illustrates the methods developed in this paper concerns the use of deadly force by police officers in the United States. Following Zimring (2017) and Sherman (2018) we have focused on law enforcement agencies, rather than cities or states, and constructed a new yearly agency-level panel of police homicides covering the period 2013-2018.

To our knowledge there have not been attempts to construct a unified database that connects lethal encounters with the characteristics of agencies and their jurisdictions. This is partly because it is extremely difficult to obtain reliable, comprehensive data on agency-level lethal encounters and other variables, such as arrests, and budgets.[29] While the FBI has made efforts to compile data on measures including arrests through the Uniform Crime Reporting Program, not all law enforcement agencies submit their reports to the FBI consistently. We believe that requiring agencies to maintain and report accurate and detailed records of these events is vitally important for researchers and policy-makers to better understand and reform police practices.

We have not addressed racial and ethnic differences in the rate at which civilians are killed by police in this paper. This is clearly a matter of the utmost policy importance and the subject of considerable public interest. The nationwide protests following the killing of George Floyd constituted possibly the largest mass action in American history, with over half a million people in more than five hundred cities at peak in June 2020 (Buchanan, Bui and Patel, 2020). Existing analyses of racial disparities in the use of deadly force—and in police practices more generally—have used data from only a handful of police departments (Hernández-Murillo and Knowles, 2004; Gelman, Fagan and Kiss, 2007; Goff et al., 2016; Fryer Jr., 2019; Hoekstra and Sloan, 2020), rather than exploiting the cross-sectional variation across all agencies. The data we have constructed for this paper is not up to the task of conducting such an analysis yet, but this is work in progress for a companion paper.

One of our main findings is that changes in both observed and/or unobserved characteristics that mimic certain agencies could result in a significant reduction in lethal encounters.

[29]Constructing a useful budget covariate does not seem feasible, as different agencies have different budgetary structures. In Newark, for instance, the maintenance of police cars is done by the Division of Motors, which is part of public works. This is somewhat surprising as police cars represent a large part of the workload of the Division of Motors. Gasoline for police cars, though, is in the police budget. Most importantly, pension and health benefits for officers are not in the police department budget. They are lumped in with other employees' benefits in the unallocated section of the city's budget.

In particular, we found that if all agencies had the observed and unobserved characteristics of the New York City Police Department, lethal encounters would be reduced from 548 to a number in the range [115,189]. This is a reduction of at least 359 lethal encounters over a six year period.

A key policy question concerns the extent to which unobserved attributes at the agency level—which we take to include selection and training protocols, promotion standards, disciplinary procedures, and organizational culture—are transferable across agencies. Certainly, some agencies have managed to achieve significant changes over time. For instance, the number of times NYPD officers discharged firearms outside of training decreased from 810 in 1971 to 52 in 2019 (City of New York Police Department, 2020), and Sherman et al. (1986) found that the police departments of the largest cities (those over 250,000 in population) reduced police homicides by around half from 1970 to 1984.

The highly decentralized nature of American policing creates challenges for statistical inference and coordinated policy response, but perhaps also opportunities for experimentation and learning. Zimring (2017) has written: "The imposing list of unanswered questions about the character and means of controlling lethal violence by police officers requires comprehensive research of quality and relevance; the control of police use of lethal violence is thus a policy emergency for scholars as well as public actors." By providing a methodology for identifying those agencies most in need of reform, and those from whom perhaps some lessons can be learned, we hope to have contributed to this program.

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A Proofs of Main Results

A.1 Proof of Proposition 1

Without loss of generality, we decompose the joint distribution of observables and unobservables using the following three terms. First, the conditional distribution of the outcome vector

$$\mathbb{P}(\mathbf{Y}_j|\mathbf{X}_j, Z_j, \alpha_j). \tag{15}$$

Second, the conditional distribution of observables given the unobservables

$$\mathbb{P}(\mathbf{X}_j, Z_j|\alpha_j). \tag{16}$$

And finally, the marginal distribution of unobserved characteristics

$$\mathbb{P}(\alpha_j). \tag{17}$$

Standard calculations show that

$$\mathbb{E}[\alpha_j|\mathbf{X}_j, \mathbf{Y}_j, Z_j] = \frac{\int \alpha \mathbb{P}(\mathbf{Y}_j|\mathbf{X}_j, Z_j\alpha)\mathbb{P}(\mathbf{X}_j, Z_j|\alpha)d\mathbb{P}(\alpha)}{\int \mathbb{P}(\mathbf{Y}_j|\mathbf{X}_j, Z_j, \alpha)\mathbb{P}(\mathbf{X}_j, Z_j|\alpha)d\mathbb{P}(\alpha)}. \tag{18}$$

Algebraic manipulations show that

$$\int \alpha \mathbb{P}(\mathbf{Y}_j|\mathbf{X}_j, Z_j\alpha_j)\mathbb{P}(\mathbf{X}_j|\alpha)d\mathbb{P}(\alpha). \tag{19}$$

$$
\begin{aligned}
&= \int \alpha \left(\Pi_{t=1}^{T} P(Y_{jt}|\mathbf{X}_j, Z_j, \alpha)\right) \mathbb{P}(\mathbf{X}_j|\alpha) d\mathbb{P}(\alpha) \\
&= \int \alpha \left(\Pi_{t=1}^{T} \frac{(\alpha\lambda_{jt})^{Y_{jt}} \exp\left(-\alpha\lambda_{jt}\right)}{Y_{jt}!}\right) \mathbb{P}(\mathbf{X}_j, Z_j|\alpha) d\mathbb{P}(\alpha) \\
&= \int \left(\frac{\alpha^{\bar{Y}_j+1}\left(\Pi_{t=1}^{T}\lambda_{jt}^{Y_{jt}}\right)\exp\left(-\alpha\bar{\lambda}_j\right)}{Y_{j1}!\dots Y_{jT}!}\right) \mathbb{P}(\mathbf{X}_j, Z_j|\alpha) d\mathbb{P}(\alpha),
\end{aligned}
$$

where $\overline{\lambda}_j$ equals $\sum_{t=1}^{T} \lambda_{jt}$.

Consider any other outcome profile $\tilde{\mathbf{Y}} \equiv (\tilde{Y}_1, \dots, \tilde{Y}_T)^\intercal$ such that

$$
\sum_{t=1}^{T} \tilde{Y}_t = \overline{Y}_j + 1. \tag{20}
$$

Dividing and multiplying the equation above by

$$
\left(\frac{\tilde{Y}_1! \dots \tilde{Y}_T!}{\Pi_{t=1}^{T}\lambda_{jt}^{\tilde{Y}_t}}\right),
$$

implies that equation (19) equals

$$
\begin{aligned}
&\left(\frac{\Pi_{t=1}^{T}\lambda_{jt}^{Y_{jt}}}{\Pi_{t=1}^{T}\lambda_{jt}^{\tilde{Y}_t}}\right)\left(\frac{\tilde{Y}_1!\dots\tilde{Y}_T!}{Y_{j1}!\dots Y_{jT}!}\right) \\
&\int \left(\frac{\alpha^{\bar{Y}_j+1}\left(\Pi_{t=1}^{T}\lambda_{jt}^{\tilde{Y}_t}\right)\exp\left(-\alpha\bar{\lambda}_j\right)}{\tilde{Y}_1!\dots\tilde{Y}_T!}\right) \mathbb{P}(\mathbf{X}_j|\alpha) d\mathbb{P}(\alpha) \\
= \; &\left(\frac{\Pi_{t=1}^{T}\lambda_{jt}^{Y_{jt}}}{\Pi_{t=1}^{T}\lambda_{jt}^{\tilde{Y}_t}}\right)\left(\frac{\tilde{Y}_1!\dots\tilde{Y}_T!}{Y_{j1}!\dots Y_{jT}!}\right) \mathbb{P}(\tilde{Y}_1, \dots, \dots \tilde{Y}_T, X_{j1}, \dots, X_{jT}, Z_j).
\end{aligned}
$$

The last line follows from the definition of marginal distribution, since

$$\begin{aligned}
\mathbb{P}(\mathbf{Y}_j, \mathbf{X}_j, Z_j) &= \int \mathbb{P}(\mathbf{Y}_j|\mathbf{X}_j, Z_j, \alpha)\mathbb{P}(\mathbf{X}_j, Z_j|\alpha)d\mathbb{P}(\alpha) \\
&= \int \left(\Pi_{t=1}^{T} \frac{(\alpha\lambda_{jt})^{Y_{jt}} \exp\left(-\alpha\lambda_{jt}\right)}{Y_{jt}!}\right) \mathbb{P}(\mathbf{X}_j, Z_j|\alpha)d\mathbb{P}(\alpha), \\
&= \int \left(\frac{\alpha^{\bar{Y}_j} \left(\pi_{t=1}^{T}\lambda_{jt}^{Y_{jt}}\right) \exp\left(-\alpha\bar{\lambda}_j\right)}{Y_{j1}!\dots Y_{jT}!}\right) \mathbb{P}(\mathbf{X}_j, Z_j|\alpha)d\mathbb{P}(\alpha).
\end{aligned}$$

Then, in the Poisson regression model given by (1)

$$\mathbb{E}[\alpha_j|\mathbf{X}_j, \mathbf{Y}_j, Z_j] =$$

$$\left(\frac{\Pi_{t=1}^{T}\lambda_{jt}(X_{jt}, \beta_{r(j)})^{Y_{jt}}}{\Pi_{t=1}^{T}\lambda_{jt}(X_{jt}, \beta_{r(j)})^{\tilde{Y}_t}}\right)\left(\frac{\tilde{Y}_1!\dots\tilde{Y}_T!}{Y_{j1}!\dots Y_{jT}!}\right)\frac{\mathbb{P}(\tilde{\mathbf{Y}}_j, \mathbf{X}_j, Z_j)}{\mathbb{P}(\mathbf{Y}_j, \mathbf{X}_j, Z_j)}. \tag{21}$$

The probability of observing a tuple $(\mathbf{Y}_j, \mathbf{X}_j, Z_j)$ for which $\overline{Y}_j = u^*$ equals

$$\begin{aligned}
\mathbb{P}(\mathbf{Y}_j, \mathbf{X}_j, Z_j) &= \mathbb{P}(\mathbf{Y}_j|\mathbf{X}_j, Z_j)\mathbb{P}(\mathbf{X}_j, Z_j) \\
&= \left[\int \left(\sum_{u=0}^{\infty} \mathbb{P}(\mathbf{Y}_j|\mathbf{X}_j, Z_j, \overline{Y}_j = u, \alpha)\mathbb{P}(\overline{Y}_j = u|\alpha, \mathbf{X}_j, Z_j)\right) d\mathbb{P}(\alpha|\mathbf{X}_j, Z_j)\right] \mathbb{P}(\mathbf{X}_j, Z_j) \\
&= \left[\int \left(\mathbb{P}(\mathbf{Y}_j|\mathbf{X}_j, Z_j, \overline{Y}_j = u^*, \alpha)\mathbb{P}(\overline{Y}_j = u^*|\alpha, \mathbf{X}_j, Z_j)\right) d\mathbb{P}(\alpha|\mathbf{X}_j, Z_j)\right] \mathbb{P}(\mathbf{X}_j, Z_j),
\end{aligned}$$

where the last inequality follows from the fact that $\mathbb{P}(\mathbf{Y}_j|\mathbf{X}_j, \overline{Y}_j = u, \alpha) = 0$, when $u \neq u^*$.

We have assumed that

$$\mathbf{P}(Y_{jt}|\mathbf{X}_j, Z_j, \alpha)$$

is a Poisson random variable with intensity parameter $\alpha\lambda_{jt}$. Therefore

$$(Y_{j1}, \dots, Y_{jT})|\mathbf{X}_j, \overline{Y}_j = u^*, \alpha \sim \text{Multinomial}\left(u^*, \left(\frac{\lambda_{j1}}{\sum_t \lambda_{jt}}, \dots, \frac{\lambda_{jT}}{\sum_t \lambda_{jt}}\right)\right),$$

which does not depend on α. Using the expression of the multinomial probability mass function implies

$$\mathbb{P}(\mathbf{Y}_j, \mathbf{X}_j, Z_j) = \left(\frac{\overline{Y}_j!}{Y_{j1}! \dots Y_{jT}!}\right) \left(\frac{\Pi_{t=1}^T \lambda_{jt}^{Y_{jt}}}{\overline{\lambda}_j^{\overline{Y}_j}}\right) \mathbb{P}(\overline{Y}_j | \mathbf{X}_j, Z_j) \mathbb{P}(\mathbf{X}_j, Z_j), \tag{22}$$

and, analogously,

$$\mathbb{P}(\tilde{\mathbf{Y}}_j, \mathbf{X}_j, Z_j) = \left(\frac{\overline{Y}_j + 1!}{\tilde{Y}_1! \dots \tilde{Y}_T!}\right) \left(\frac{\Pi_{t=1}^T \lambda_{jt}^{\tilde{Y}_t}}{\overline{\lambda}_j^{\overline{Y}_j + 1}}\right) \mathbb{P}(\overline{Y}_j + 1 | \mathbf{X}_j, Z_j) \mathbb{P}(\mathbf{X}_j, Z_j). \tag{23}$$

Consequently,

$$\frac{\mathbb{P}(\tilde{\mathbf{Y}}_j, \mathbf{X}_j, Z_j)}{\mathbb{P}(\mathbf{Y}_j, \mathbf{X}_j, Z_j)} = \left(\frac{Y_{j1}! \dots Y_{jT}!}{\tilde{Y}_1! \dots \tilde{Y}_T!}\right) \left(\frac{\overline{Y}_j + 1}{\overline{\lambda}_j}\right) \left(\frac{\Pi_{t=1}^T \lambda_{jt}^{\tilde{Y}_t}}{\Pi_{t=1}^T \lambda_{jt}^{Y_{jt}}}\right) \frac{\mathbb{P}(\overline{Y}_j + 1 | \mathbf{X}_j, Z_j)}{\mathbb{P}(\overline{Y}_j | \mathbf{X}_j, Z_j)}. \tag{24}$$

The last equation implies

$$\mathbb{E}[\alpha_j | \mathbf{Y}_j, \mathbf{X}_j, Z_j] = \frac{\overline{Y}_j + 1}{\overline{\lambda}_j} \cdot \frac{\mathbb{P}(\overline{Y}_j + 1 | \mathbf{X}_j, Z_j)}{\mathbb{P}(\overline{Y}_j | \mathbf{X}_j, Z_j)},$$

where

$$\bar{\lambda}_j \equiv \exp(\gamma^\intercal Z_j) \exp\left(X_{jt}^\intercal \beta\right)$$

Posterior Mean in the Binomial Regression Model for Count Panel Data

We proceed as before and derive an expression for

$$\int \alpha \mathbb{P}(\mathbf{Y}_j | \mathbf{X}_j, \alpha_j) \mathbb{P}(\mathbf{X}_j | \alpha) d\mathbb{P}(\alpha)$$

in terms of the marginal distribution of outcomes and observables. For any $\mathbf{Y}_j$ and $\mathbf{X}_j$ and any $\tilde{\mathbf{Y}}_j$, $\tilde{\mathbf{X}}_j$ in $\widetilde{\mathcal{Y}}(\mathbf{Y}_j, \mathbf{X}_j)$

$$\int \alpha \mathbb{P}(\mathbf{Y}_j | \mathbf{X}_j, \alpha_j) \mathbb{P}(\mathbf{X}_j | \alpha) d\mathbb{P}(\alpha)$$

$$
\begin{aligned}
&= \int \alpha \left(\Pi_{t=1}^{T} P(Y_{jt}|\mathbf{X}_j, \alpha)\right) \mathbb{P}(\mathbf{X}_j|\alpha) d\mathbb{P}(\alpha) \\
&= \int \alpha \left(\Pi_{t=1}^{T} \frac{X_{1,jt}!}{(X_{1,jt} - Y_{jt})! Y_{jt}!} (\alpha\lambda_{jt})^{Y_{jt}} (1 - \alpha\lambda_{jt})^{X_{1,jt} - Y_{jt}}\right), \\
&\quad \mathbb{P}(\mathbf{X}_{j1}|\mathbf{X}_{j2}, \dots \mathbf{X}_{jK}) \mathbb{P}(\mathbf{X}_{j2}, \dots, \mathbf{X}_{jk}|\alpha) d\mathbb{P}(\alpha) \\
&\quad \text{(by equation (14))} \\
&= \int \alpha^{\bar{\tilde{\mathbf{Y}}}_j} \left(\Pi_{t=1}^{T} \frac{X_{1,jt}! \lambda_{jt}^{Y_{jt}}}{(\tilde{X}_{1,jt} - \tilde{Y}_{jt})! Y_{jt}!} (1 - \alpha\lambda_{jt})^{\tilde{X}_{1,jt} - \tilde{Y}_{jt}}\right) \\
&\quad \mathbb{P}(\tilde{\mathbf{X}}_{j1}|\mathbf{X}_{j2}, \dots \mathbf{X}_{jK}) \mathbb{P}(\mathbf{X}_{j2}, \dots, \mathbf{X}_{jk}|\alpha) d\mathbb{P}(\alpha) \\
&\quad \text{(by Assumptions 1, 2 and 3 above)} \\
&= \Pi_{t=1}^{T} \frac{X_{1,jt}! \lambda_{jt}^{Y_{jt}} \tilde{Y}_{jt}!}{\tilde{X}_{1,jt}! \lambda_{jt}^{\tilde{Y}_{jt}} Y_{jt}!} \mathbb{P}(\tilde{\mathbf{Y}}_j, \tilde{\mathbf{X}}_{1j}, \mathbf{X}_{2j}, \dots, \mathbf{X}_{kj}).
\end{aligned}
$$

A.2 Nonparametric Bootstrap CIs

The confidence intervals reported in Section 5 were constructed by sampling values of $(\widehat{\beta}, \widehat{\gamma})$ from their estimated asymptotic distribution. We evaluated the counterfactual of interest at each value, and reported the 5% and 95% quantiles of the resulting distribution.

We recompute the confidence intervals reported in Section 5 by using a nonparametric bootstrap. We sample $(\mathbf{X}_j, Y_j, Z_j)$ from their empirical distribution, excluding the 10 agencies that are used in the counterfactuals. We construct a new data set of 7,609 and for each new data set (we consider 1,000 of them) we estimate β and γ. We then evaluate the counterfactual of interest at each value, and report the 5% and 95% quantiles of the resulting distribution.

Table 5: Counterfactual police homicides for 2013-2018: Unobserved Covariates

	Phoenix	Las Vegas	Dallas	Philadelphia	San Diego	Chicago	Los Angeles	Houston	San Antonio	New York
Phoenix	**93**	[60,70]	[51,79]	[44,98]	[50,73]	[47,80]	[44,60]	[43,54]	[38,61]	[13,36]
Las Vegas	[70,81]	**51**	[40,63]	[35,79]	[41,58]	[38,66]	[34,51]	[34,44]	[30,51]	[10,30]
Dallas	[41,63]	[28,45]	**33**	[28,45]	[26,39]	[25,44]	[23,34]	[22,31]	[24,29]	[8,17]
Philadelphia	[28,61]	[19,43]	[22,35]	**28**	[20,36]	[21,34]	[17,30]	[16,29]	[16,29]	[7,12]
San Diego	[35,51]	[24,35]	[24,35]	[22,40]	**26**	[22,36]	[20,27]	[19,25]	[18,28]	[6,14]
Chicago	[75,128]	[51,88]	[50,87]	[55,89]	[48,78]	**63**	[45,66]	[41,60]	[37,71]	[16,35]
Los Angeles	[177,244]	[116,172]	[113,171]	[110,191]	[113,152]	[110,163]	**113**	[94,123]	[88,130]	[33,69]
Houston	[90,114]	[61,80]	[56,81]	[53,96]	[56,73]	[55,81]	[48,63]	**51**	[42,66]	[15,37]
San Antonio	[55,88]	[37,62]	[42,52]	[36,67]	[35,55]	[33,63]	[31,46]	[28,44]	**35**	[11,24]
New York	[145,402]	[98,281]	[110,229]	[131,221]	[105,234]	[103,227]	[92,191]	[80,196]	[84,177]	**55**
Totals	[835,1287]	[564,906]	[591,798]	[582,881]	[556,764]	[549,792]	[517,618]	[460,628]	[442,627]	[178,323]

Note: Diagonal entries are observed lethal encounters (totaling 548 encounters). Off-diagonal entries are 90% confidence intervals for counterfactual values of lethal encounters, obtained by replacing the posterior expectation of α_j for the agency in the row with that of the agency in the column, while assuming no change in observed covariates. Agencies are listed in decreasing order by their estimated value of α_j.

Table 6: Counterfactual police homicides for 2013-2018: Observed Covariates

	Phoenix	San Antonio	Las Vegas	Los Angeles	Houston	Dallas	San Diego	Chicago	Philadelphia	New York
Phoenix	**93**	[66,80]	[71,81]	[57,76]	[55,71]	[51,68]	[41,60]	[33,58]	[24,52]	[19,44]
San Antonio	[42,51]	**35**	[34,43]	[29,35]	[28,34]	[26,32]	[23,27]	[17,28]	[13,24]	[10,20]
Las Vegas	[60,69]	[44,56]	**51**	[38,53]	[37,49]	[35,47]	[28,40]	[22,40]	[17,36]	[12,30]
Los Angeles	[141,189]	[117,140]	[111,156]	**113**	[95,119]	[89,114]	[77,98]	[63,91]	[47,80]	[37,67]
Houston	[69,89]	[55,68]	[55,72]	[50,62]	**51**	[48,51]	[36,49]	[29,44]	[23,38]	[17,33]
Dallas	[47,63]	[38,47]	[38,50]	[34,44]	[35,37]	**33**	[25,33]	[20,30]	[16,26]	[12,23]
San Diego	[42,61]	[36,43]	[35,50]	[31,40]	[29,39]	[27,37]	**26**	[18,30]	[14,26]	[11,21]
Chicago	[104,183]	[83,139]	[83,152]	[80,117]	[76,113]	[72,108]	[57,96]	**63**	[43,60]	[33,51]
Philadelphia	[53,111]	[43,82]	[42,91]	[41,70]	[40,66]	[38,62]	[30,56]	[31,43]	**28**	[20,29]
New York	[119,284]	[99,208]	[96,237]	[96,172]	[87,172]	[83,163]	[71,135]	[71,107]	[57,81]	**55**
Totals	[783,1169]	[644,867]	[626,961]	[619,723]	[569,706]	[535,676]	[445,595]	[389,500]	[300,435]	[228,368]

Note: Diagonal entries are observed lethal encounters (totaling 548 encounters). Off-diagonal entries are 90% confidence intervals for counterfactual values of lethal encounters, obtained by replacing Officers per 1k population, Gun Death Rate, Share in Poverty, Garner, and LEOBR of the agency in the row with that of the agency in the column. Agencies are listed in decreasing order by the estimated effect of these covariates, so entries decline as one reads across rows.

Table 7: Counterfactual police homicides for 2013-2018: Unobserved and Observed

	Phoenix	Las Vegas	Dallas	San Antonio	Los Angeles	Houston	San Diego	Chicago	Philadelphia	New York
Phoenix	**93**	[51,53]	[32,48]	[31,46]	[33,40]	[31,33]	[31,34]	[26,32]	[20,31]	[5,9]
Las Vegas	[92,96]	**51**	[32,48]	[30,46]	[33,40]	[30,33]	[30,33]	[26,31]	[20,30]	[5,9]
Dallas	[67,99]	[37,55]	**33**	[32,34]	[27,37]	[23,33]	[22,33]	[20,30]	[20,22]	[5,7]
San Antonio	[73,110]	[41,61]	[36,39]	**35**	[30,41]	[25,37]	[25,37]	[22,34]	[22,25]	[5,8]
Los Angeles	[269,324]	[149,181]	[104,146]	[99,139]	**113**	[94,107]	[90,111]	[79,98]	[65,93]	[17,28]
Houston	[146,159]	[81,89]	[53,77]	[51,74]	[55,63]	**51**	[48,56]	[43,49]	[33,49]	[8,15]
San Diego	[76,83]	[42,46]	[27,41]	[26,39]	[28,34]	[25,29]	**26**	[21,28]	[17,26]	[4,8]
Chicago	[191,235]	[106,130]	[72,107]	[68,104]	[75,92]	[68,77]	[62,83]	**63**	[46,66]	[11,21]
Philadelphia	[89,135]	[50,75]	[44,49]	[41,48]	[35,51]	[31,45]	[30,46]	[28,40]	**28**	[7,10]
New York	[556,1066]	[309,594]	[266,392]	[259,369]	[232,383]	[193,356]	[188,362]	[170,324]	[165,245]	**55**
Totals	[1682,2371]	[932,1311]	[750,909]	[716,865]	[693,855]	[586,789]	[564,800]	[510,708]	[467,577]	[123,169]

Note: Diagonal entries are observed lethal encounters (totaling 548 encounters). Off-diagonal entries are 90% confidence intervals for counterfactual values of lethal encounters, obtained by replacing the posterior expectation of α_j for the agency in the row with that of the agency in the column, while assuming no change in observed covariates. Agencies are listed in decreasing order by their estimated value of α_j.

A.3 Assaults

In the main body of the paper we have interpreted the unobserved agency-specific covariates as the agencies' selection practices, training, and culture. One argument against this interpretation is that our econometric model does not include any variable that controls for the level of threat faced by officers in enforcing the law. To address this concern we used the Law Enforcement Officers Killed and Assaulted (UCR-LEOKA) data set to extract a time-varying measure of armed and unarmed assaults against police officers. There are several measurement issues with this variable, including the fact that some of the largest police departments in our data set (including the New York City Police Department and the Chicago Police Department) report no assaults on police officers over the period 2013-2018.

Table 8 shows that the coefficient on assaults per officer is not statistically different from zero. Moreover, the inclusion of assaults per officer barely affects the results reported in the main body of the paper.

Table 8: Coefficient Estimates

	Coefficient	Standard Errors
Murder per pop. (in hundred thousands)	0.004	0.008
Assaults per Officer (in tens)	0.077	0.104
Log of Avg. pop. (in millions)	1.192	0.106
Officers per pop. (in thousands)	0.013	0.004
Gun Death Rate (%)	0.047	0.017
Share in Poverty (%)	0.038	0.014
Share Black (%)	-0.022	0.008
Garner	-0.059	0.237
LEOBR	-0.084	0.214
Land Area (sq. km.) per pop. (in millions)	1.0318e-05	1.7834e-06

Table 9 also reports counterfactual police homicides for 2013-2018 based on changes in the agencies' unobserved covariates. The best and worst performing agency (ranked by the posterior mean of α_j) remains the same, with the New York City Police Department and the Phoenix Police Department at opposite ends of the table. The ranking for most of the other agencies also remains unchanged (with the exception of Chicago, Philadelphia, Los Angeles, and San Diego). Excluding New York and Chicago, the number of assaults reported by each department to LEOKA is strictly positive. Consequently, it is not surprising to see the unobserved covariates of the Chicago Police Department become less favorable than before the inclusion of the assaults covariate. Similarly, the Los Angeles Police Department has 0.778 assaults per 10 officers, while the San Diego Police Department has 1.8470. This means that officers in the San Diego Police Department have a higher risk of assault, and as a result, the unobserved covariates get more credit for the relatively low number of lethal encounters. Lastly, Table 10 reports counterfactuals based on observed characteristics, while

11 reports counterfactuals based on observed and unobserved covariates.

Table 9: Counterfactual police homicides for 2013-2018: Unobserved Covariates

	Phoenix	Las Vegas	Dallas	Chicago	Philadelphia	San Diego	Los Angeles	Houston	San Antonio	New York
Phoenix	**93**	[55,116]	[45,109]	[42,103]	[36,106]	[47,77]	[38,85]	[39,73]	[35,70]	[11,43]
Las Vegas	[42,89]	**51**	[31,66]	[33,55]	[22,75]	[28,55]	[29,46]	[28,44]	[20,50]	[8,24]
Dallas	[29,70]	[27,58]	**33**	[22,48]	[22,42]	[20,42]	[18,42]	[19,36]	[19,30]	[7,15]
Chicago	[58,143]	[60,102]	[46,101]	**63**	[38,96]	[42,79]	[41,73]	[45,61]	[29,79]	[12,33]
Philadelphia	[26,77]	[20,67]	[23,45]	[19,49]	**28**	[19,43]	[15,50]	[16,40]	[15,35]	[6,17]
San Diego	[33,54]	[26,50]	[22,46]	[22,41]	[18,42]	**26**	[18,37]	[20,31]	[15,32]	[5,17]
Los Angeles	[126,286]	[130,204]	[92,212]	[99,177]	[66,228]	[82,175]	**113**	[87,138]	[60,155]	[27,66]
Houston	[67,124]	[62,95]	[49,95]	[54,74]	[38,92]	[46,71]	[43,68]	**51**	[30,72]	[12,34]
San Antonio	[48,97]	[38,94]	[40,65]	[29,80]	[30,69]	[30,64]	[26,68]	[26,61]	**35**	[9,26]
New York	[121,496]	[122,369]	[125,281]	[108,293]	[97,272]	[90,285]	[96,232]	[86,237]	[79,218]	**55**
Totals	[690,1468]	[656,1101]	[586,942]	[548,885]	[430,1000]	[480,851]	[490,739]	[479,693]	[374,720]	[161,316]

Note: Diagonal entries are observed lethal encounters (totaling 548 encounters). Off-diagonal entries are 90% confidence intervals for counterfactual values of lethal encounters, obtained by replacing the posterior expectation of α_j for the agency in the row with that of the agency in the column, while assuming no change in observed covariates. Agencies are listed in decreasing order by their estimated value of α_j.

Table 10: Counterfactual police homicides for 2013-2018: Observed Covariates

	Phoenix	Las Vegas	San Antonio	Los Angeles	Houston	Dallas	Chicago	San Diego	Philadelphia	New York
Phoenix	**93**	[67,85]	[66,84]	[62,84]	[52,82]	[48,80]	[38,76]	[41,68]	[25,74]	[23,62]
Las Vegas	[57,73]	**51**	[46,59]	[43,58]	[38,54]	[35,52]	[28,48]	[30,45]	[19,48]	[16,41]
San Antonio	[40,51]	[32,41]	**35**	[34,36]	[27,37]	[25,35]	[20,33]	[22,30]	[13,33]	[12,27]
Los Angeles	[128,173]	[102,137]	[114,122]	**113**	[90,117]	[83,113]	[66,107]	[73,95]	[45,104]	[41,85]
Houston	[59,94]	[50,71]	[51,69]	[51,66]	**51**	[48,51]	[37,48]	[36,49]	[25,47]	[22,40]
Dallas	[40,67]	[34,50]	[35,49]	[34,46]	[35,37]	**33**	[27,32]	[25,34]	[18,32]	[16,27]
Chicago	[79,159]	[69,119]	[69,117]	[68,110]	[69,89]	[67,82]	**63**	[52,78]	[42,65]	[37,57]
San Diego	[37,62]	[31,47]	[33,44]	[32,42]	[29,39]	[27,37]	[22,34]	**26**	[15,32]	[15,26]
Philadelphia	[37,108]	[31,81]	[32,78]	[32,73]	[32,60]	[31,55]	[29,44]	[24,53]	**28**	[21,30]
New York	[85,234]	[71,177]	[75,164]	[75,154]	[72,131]	[70,121]	[63,97]	[59,104]	[54,76]	**55**
Totals	[666,1105]	[555,834]	[581,790]	[579,743]	[558,626]	[526,588]	[426,540]	[422,536]	[289,530]	[263,445]

Note: Diagonal entries are observed lethal encounters (totaling 548 encounters). Off-diagonal entries are 90% confidence intervals for counterfactual values of lethal encounters, obtained by replacing Officers per 1k population, Gun Death Rate, Share in Poverty, Garner, and LEOBR of the agency in the row with that of the agency in the column. Agencies are listed in decreasing order by the estimated effect of these covariates, so entries decline as one reads across rows.

Table 11: Counterfactual police homicides for 2013-2018: Unobserved and Observed

	Phoenix	Las Vegas	Dallas	Los Angeles	San Antonio	Houston	Chicago	San Diego	Philadelphia	New York
Phoenix	**93**	[42,96]	[29,75]	[28,68]	[27,56]	[27,53]	[23,61]	[28,41]	[19,44]	[4,19]
Las Vegas	[51,116]	**51**	[26,54]	[30,42]	[19,50]	[27,35]	[26,35]	[21,35]	[15,35]	[4,12]
Dallas	[42,109]	[33,67]	**33**	[22,46]	[23,36]	[20,38]	[19,41]	[17,36]	[19,24]	[4,10]
Los Angeles	[157,383]	[143,197]	[84,174]	**113**	[63,162]	[85,115]	[83,116]	[66,117]	[49,112]	[15,35]
San Antonio	[60,124]	[37,97]	[34,53]	[25,65]	**35**	[23,53]	[21,58]	[22,45]	[22,31]	[5,14]
Houston	[93,180]	[78,99]	[46,90]	[52,70]	[35,81]	**51**	[44,61]	[39,56]	[28,57]	[7,20]
Chicago	[99,258]	[94,129]	[53,117]	[63,88]	[39,112]	[55,76]	**63**	[41,82]	[31,75]	[9,25]
San Diego	[62,92]	[40,65]	[26,54]	[26,47]	[22,44]	[25,36]	[21,42]	**26**	[16,33]	[4,13]
Philadelphia	[62,142]	[43,99]	[41,53]	[29,67]	[34,46]	[27,54]	[25,59]	[24,50]	**28**	[5,15]
New York	[282,1306]	[245,709]	[195,453]	[181,434]	[143,442]	[144,415]	[144,402]	[114,416]	[112,310]	**55**
Totals	[1043,2750]	[898,1496]	[655,1021]	[652,933]	[477,1001]	[531,856]	[515,877]	[436,861]	[379,674]	[114,210]

Note: Diagonal entries are observed lethal encounters (totaling 548 encounters). Off-diagonal entries are 90% confidence intervals for counterfactual values of lethal encounters, obtained by replacing Officers per 1k population, Gun Death Rate, Share in Poverty, Garner, LEOBR, and the posterior expectation of α_j of the agency in the row with that of the agency in the column. Agencies are listed in decreasing order by the estimated effect of these covariates, so entries decline as one reads across rows.