How Private Prisons Affect Incarceration Likelihood

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1 Introduction

Privately-owned prisons recently emerged as a prominent political issue. A 2016 Department of Justice (DOJ) Inspector General report found "contract prisons incurred more safety and security incidents per capita than comparable [federal Bureau of Prisons] institutions" with heightened levels of lockdowns, property damage, contraband smuggling, and inmate and staff assault (Office of the Inspector General, 2016). The DOJ soon after announced current federal contracts to privately-owned prisons would not be renewed upon expiration or would be renewed with "substantially" lower contracted usage. Incoming Attorney General Jeff Sessions rescinded this policy soon after his early 2017 Senate confirmation.

The American Civil Liberties Union (ACLU) alleges private prisons contribute to increasing the national incarceration rate (Shapiro, 2011) through lobbying and direct contributions to individuals in exchange for policies which increase incarceration rates (Ashton and Petteruti, 2011). In the 2011 Luzerne County, Pennsylvania "Kids for Cash" scandal, two judges were convicted of taking over $2.6 million from private facilities in exchange for harsher juvenile offender sentences. Private prisons lobby for contractual minimum occupancies, where private prisons must be reimbursed for carrying empty beds below an agreed threshold, and the Immigrations and Customs Enforcement (ICE) "bed quota" wherein ICE must maintain a minimum of 34,000 inmates regardless of illegal immigration levels. Private prisons comprise nine of the ten largest ICE detention centers (Ashton and Petteruti, 2011).

Galinato and Rohla (2017) test this mechanism using a common agency framework (Grossman and Helpman, 1994), finding the number of private prisons relates to increases in incarceration over probation for drug, public order, and property crimes in states with higher corruption conviction rates. When there exists little room for expansion in proportion of convicts sentenced to prison, the private prison-lobbying mix may increase average sentence lengths, such as for immigration and weapons crimes. However, its use of aggregate data makes it unable to address a more fundamental question: when a convicted criminal is sentenced by a judge, does the influence of private prison lobbying affect the likelihood by with which this convict is sentenced to prison over probation? Only by the use of individual-level data can this question be more fully teased out.

This chapter's results broadly support previous literature with added nuance. Calculated marginal effects of an additional private prison on incarceration likelihood reinforce that private prisons only create harmful impacts on sentencing decisions when enforcement agents are susceptible to lobbying. Incarceration likelihood for "lesser" crime types such as property, drug, and public order crimes are increased much more by private prison presence than violent or immigration crimes. Results indicate the groups most harmed are those traditionally less likely to be sent to prison: women, those who have completed high school and college, American citizens, and those without criminal history. Results are directionally robust to using private prison occupancy size as a rather than number of institutions.

1.1 Literature

Literature on private prisons comprises four main strands: standards of inmate care, government cost savings, recidivism rates, and economic growth of local jurisdictions (Hartney and Glesmann, 2012). The question of potential government cost savings stands as the most widely researched. Studies to support practically every position exist: private prisons are no more cost-effective than public prisons (Pratt and Maahs, 1999), private prisons save 10-15% on operations costs (Moore, 1998), any cost savings come at the detriment of staff and training quality (Mason, 2012), private firms manufacture "savings" by accounting for capital costs throughout asset life (Gregson, 2000), and private prisons achieve savings through stronger increasing returns to scale than public prisons (Merryman, 2001).

Recidivism studies paint a more uniformly negative picture of private prisons. Mukherjee's (2016) staggered prison occupancy shock model calculates Mississippi private prisons inmates serve an average of 90 additional days in person due to conduct violations than prisoners in comparable public prisons without any associated reduction in recidivism. Spivak and Sharp (2008) find Oklahoma prisoners faced a greater hazard of recidivism when placed in a privately-owned prison over a state-run prison, a finding replicated in Minnesota by Duwe and Clark (2013). Three Florida-based studies in the 1990s and 2000s purporting lower recidivism rates and cost savings for private prisons were discredited on account of improperly-disclosed payments by private prison firms to their author Charles Thomas.

Literature on standards of inmate care in private prisons has varied over time. While early research on quality of confinement suggested firms could improve on public prisons (Brakel, 1988; Logan, 1992), subsequent reports and lawsuits regarding inmate health care (Joint Legislative Audit Review Commission, 1994; Massey, 2000; St. John, 2015), mental health care (Daniel, 2007), and threat of harm and violence to inmates (Blades, 2008; Newkirk and Selway, 2013) combined with the 2016 DOJ report suggest this capacity has been poorly realized subsequently. A brief by advocacy group In the Public Interest connects “violent atmospheres” in private prisons to recidivism outcomes (In the Public Interest, 2016). Chen and Shapiro (2007) find harsher prison conditions may relate to higher post-release crime rates.

1.2 Contributions

This chapter contributes to two fields of literature in addition to the direct discourse on private prisons. It will contribute to the empirical literature on determinants of sentencing decisions, which plays a foundational role in isolating the impact of any measurable private prison influence. Second, this chapter will contribute to the theoretical literature on judicial sentence decision-making, particularly when confronted with the prospect of convict recidivism.

Without first accounting for factors known to influence judicial decisions, any estimated effect of private prisons may be subject to omitted variable bias. Literature has focused on race (Leiber and Blowers, 1993; Everett and Wojtkiewicz, 2002; Doerner and Demuth, 2009) and sex discrepancies (Nagel and Hagan, 1983; Doerner and Demuth, 2009) in criminal sentencing. Intense local political and spatial demographic factors (Helms, 2009) and the impact of the individual judge characteristics (Johnson, 2006) also play roles. Defendant criminal history (Roberts, 1996), educational background (Mustard, 2001), income level and socioeconomic status (Miethe and Moore, 1985; D'Alessio and Stolzenberg, 1993), number of children and family roles (Bickle and Peterson, 2014), age (Steffensmeier and Motivans, 2000; Doerner and Demuth, 2009), and citizenship status (Demuth, 2002) all influence sentencing outcomes, and the extent of their impact asymmetrically varies by crime type (Rodriguez et al., 2006). These studies generally agree racial minorities, men, the poor, those without college degrees, and the young tend to receive harsher sentences than their converses (Mustard, 2001; Doerner and Demuth, 2009), both in terms of the prison-probation decision and overall sentence length.[1] This chapter contributes to this literature by incorporating heretofore unaccounted for variables–private prisons and their interaction with lobby-influenced judicial processes–and by providing further nuance to the broad findings on defendant demographic influence on sentencing decisions.

Theoretical literature on judicial sentence decision-making dates to Becker (1968), who modeled criminal activity supply and demand. Economic analysis of optimal criminal sanctions often addresses

[1] Local political and demographic patterns sometimes upend these broad findings. For example, in counties with black majority populations, evidence indicates that white convicts tend to receive harsher sentences while black convicts receive more lenient outcomes without a change for other races or ethnicities (Helms, 2009; Myers and Talarico, 2014)

designing punishments to deter recidivism and repeat offenses (Eide et al., 2006). Penal law treats first offenses more harshly than secondary offenses, but this design has received mixed support in theoretical literature (Chu et al., 2000). Miceli and Bucci (2005) offer support for escalating sanctions based on convict opportunity costs and diminishing future wage potential. Miceli (2013) employs judicial uncertainty about future gains as a motivation for increasing penalties whereas Emons (2003) argues for maximal initial penalties with no future sanction. Emons (2004, 2007) generalizes his own findings using game theory to be conditional on the amount of benefit received by the criminal.

This chapter draws upon many aspects of the aforementioned papers, namely using a game theoretic framework wherein the judge seeks to minimize future recidivism prospects despite incomplete information and deter potential outside offenders. The opportunity costs described by Miceli and Bucci play a key role in the decision-making process of both agents in the model presented here. This paper also expands on previous literature through incorporating a corrupt judicial authority who creates a sentencing rule for both their own sake and for society's benefit.

1.3 Contents

This chapter is structured as follows: Section 2 presents a theoretical model explaining lobby-influenced judicial sentencing behavior and its effect on incarceration likelihood. Section 3 discusses an empirical method for testing the predictions of the previous section. Section 4 expounds on the data which will be used in the empirical specification. Section 5 presents empirical results, and Section 6 offers ideas for where next to take the chapter.

2 Theoretical Model

The following model presents the sentencing decision-making process for a single convict by a judge influenced by an outside private prison lobbying group. The interaction between the three agents comprises a sequential two-stage game with the following stages:

First Stage: The judge adjudicates an individual case for a convict who has been found guilty of committing a crime. They issue a sentence designed to balance their personal welfare from the lobby group contract and minimizing future harm to society through recidivism despite not knowing the probability the convict will commit an additional crime.

Stage Stage: Upon completion of their sentence, the convict decides whether to commit a secondary crime in order to maximize lifetime welfare.

Interaction between the judge and the lobby group occurs concurrent with first stage of the game. The lobby group offers the judge a certain amount of money in exchange for prison sentences. The judge incorporates this offer into their payoff structure within the game.

2.1 Assumptions

2.1.1 The Judge

- Maximizes the weighted sum of their personal welfare and societal welfare.
- Places weight $\phi \geq 0$ on their personal welfare.
- Assigns the convict found guilty of a crime of severity $\psi \in [0, 1]$ to either a prison sentence of length $s \in (0, 1]$ or a probation sentence of length $s = 0$.
- Sentencing the convict to prison creates a "deterrence externality" D reducing the incentives for others to commit crimes (Landes and Posner, 1975; Levitt, 1998; Katz et al., 2003). The value of D is a function of s,ψ, and the convict's demographics and history x. By assumption, $\frac{\partial D}{\partial s}, \frac{\partial D}{\partial \psi} > 0$. D is concave for each individual input, but all complement each other (Bar-Gill and Harel, 2001).
- During the time s for which the convict is sentenced to prison, the convict can not commit another crime against society, creating a period of "peace" which is valued at $P > 0$.
- The marginal cost of incarceration is $c > 0$.

2.1.2 The Convict

- Maximizes welfare of one-period lifetime.
- Can earn wage $w > 0$ if outside prison.
- Incurs marginal harm $h > 0$ during s due to opportunity costs, social isolation and stigma, lost future wage gains, and possible prison-related abuse or violence (Miceli and Bucci, 2005).
- If they choose to commit another crime, they gain $G \geq 0$ from their crime, but will earn an additional prison sentence of length $z > 0$ at probability $q > 0$ which is a function of ψ and x. Assume $\frac{\partial q}{\partial \psi} > 0$.
- The true value of G is unknown to the judge, but is known to the convict. Nature determines the value of G to be either high such that $G = G_H$ or low such that $G = 0$.

- G_H is sufficiently large such that there plausibly exists a positive incentive to commit a secondary crime, such that $G_H > (w + hz)q(\psi, x)$, as otherwise there exists no threat of recidivism.

- Nature determines that $G = G_H$ will occur with probability $\theta_0 \in [0, 1]$. The judge does not know the true value of θ, but can observe the expected value given initial crime severity and demographics $\theta = E(\theta_0|\psi, x)$.

- If indifferent between recidivizing and not recidivizing, the convict will not commit the secondary crime.

2.1.3 The Prison Lobby

- There exists a private prison industry composed of $n > 0$ identical firms.

- Firms receive contracts from the government to house convicts sentenced to prison.

- They receive a contracted per-prisoner rate $c > 0$ and use the prisoners to engage in production of a consumption good sold at price $p > 0$.

- The industry's production function f from an individual prisoner is a function of the size of the lobby n and sentence length s. n acts as a capital input while s acts a labor input.

- f is increasing and concave in both n and s. Assume s and n are complements such that $\frac{\partial^2 f}{\partial s \partial n} > 0$.

- Incurs operation and housing cost $c_L < c$.

- This lower cost comes at an increase in harm h to a prisoner housed in their institution. *Ceteris paribus*, an increase in n will increase the probability of being incarcerated in a private prison if given a prison sentence, implying $\frac{\partial h}{\partial n} > 0$ (Mason, 2012; Austin and Coventry, 2001).

- The n firms band together to form a lobby group to influence the judge's sentencing rule. Their lobby schedule offer to the judge is $\lambda \geq 0$.

2.2 Private Prison Industry

The lobby has the following profit function for a given prisoner:

$$W_L \equiv pf(n, s) + (c - c_L)s - \lambda \tag{1}$$

The lobby group's first order condition with respect to λ is

$$p\frac{\partial f(n,s)}{\partial s}\frac{\partial s}{\partial \lambda} + (c - c_L)\frac{\partial s}{\partial \lambda} - 1 = 0 \tag{2}$$

which, assuming the monotonicity of λ, yields Grossman and Helpman's (1994) local truthfulness condition describing the optimal lobby schedule:

$$\frac{\partial \lambda}{\partial s} = p\frac{\partial f(n,s)}{\partial s} + (c - c_L) \tag{3}$$

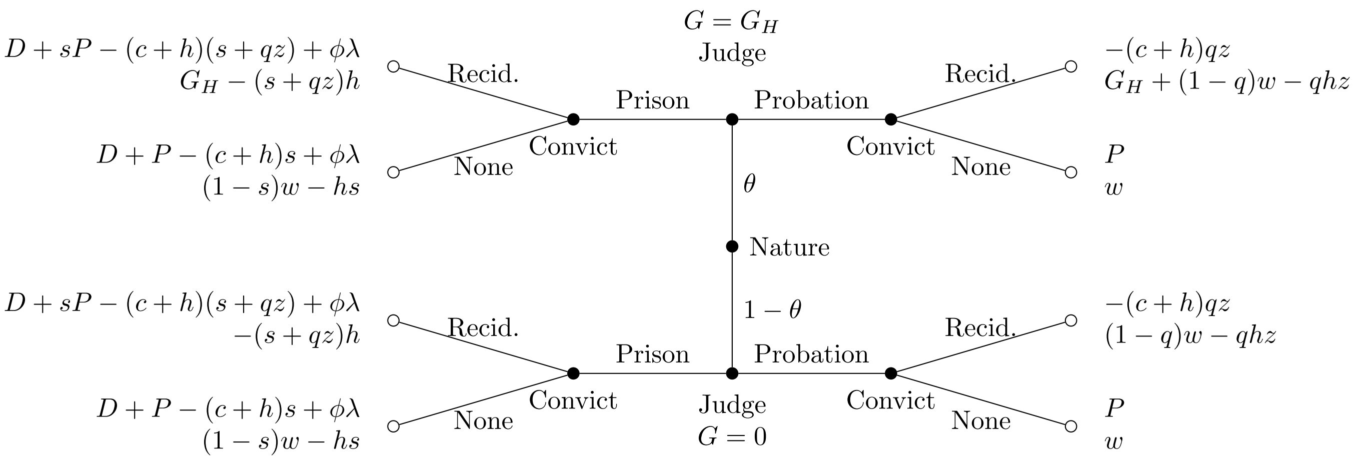
wherein the lobby group will increase their offer for additional sentence length in accordance to their marginal profit from an additional unit of s.

The slope of the lobby schedule with respect to the size of the lobby is determined by a parallel procedure:

$$\frac{\partial \lambda}{\partial n} = p\frac{\partial f(n,s)}{\partial n} \tag{4}$$

2.3 Sentencing Game

The sentencing game between the judge and convict can be represented in extensive form where the first row represents payoffs to the judge and the second row payoffs for the convict:



Despite a similar construction, this is not a true signaling game as the only observable signals sent by the convict are exogenously determined prior to its start. The Bayesian Nash equilibrium of this game can solved for through backward induction.

2.3.1 The Convict's Decision

Consider the following possible cases:

Type Low, Probation: The convict will choose not to recidivize as $w \geq (1-q(\psi,x))w - q(\psi,x)h(n)z$ for all permissible parameter values.

Type Low, Prison: The convict will choose not to recidivize as $(1-s)w-h(n)s \geq -(s+q(\psi,x)z)h$ for all permissible parameter values.

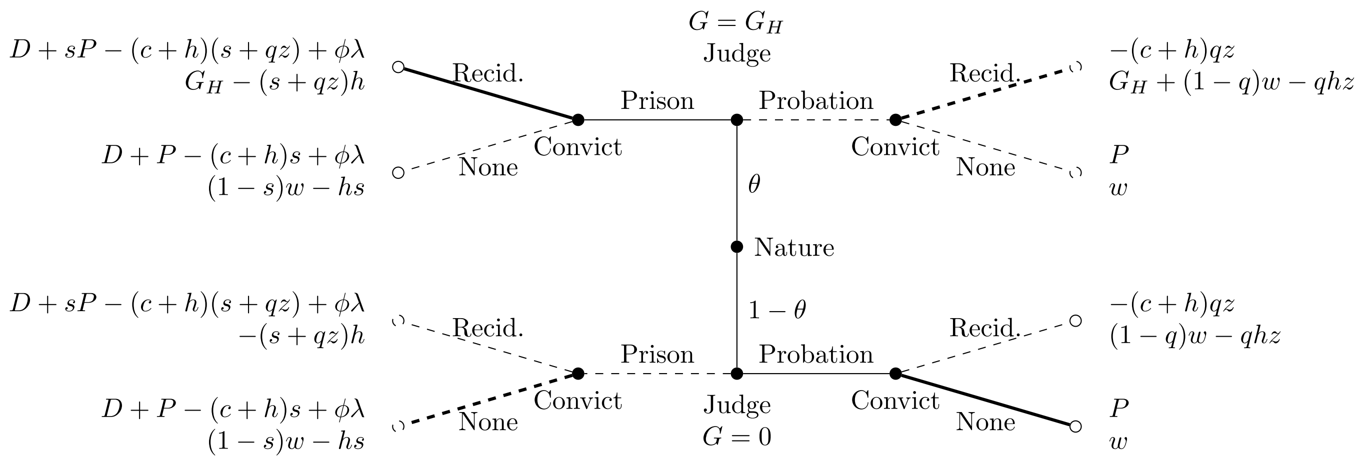
Type High, Probation: Given the assumption that $G_H > (w+h(n)z)q(\psi,x)$, it follows that $G_H + (1-q(\psi,x))w - q(\psi,x)h(n)z = G_H - (w+h(n)z)q(\psi,x) + w > w$ for all permissible parameter values, meaning the convict will choose to recidivize.

Type High, Prison: The convict will certainly choose to recidivize based on $G_H > (w + h(n)z)q(\psi,x)$ if $q > 1-s$. If $q \leq 1-s$, they will still choose to recidivize if $G > (1-s)w + qhz$.

Altogether, if $q > 1-s$, the convict will always recidivize if type $G = G_H$ and never if type $G = 0$.

2.3.2 The Judge's Decision

Assume s is fixed. With these responses known, the judge will choose to sentence a convict for whom $G = G_H$ to prison as long as $D + sP + \phi\lambda > (c+h(n))s$, provided they knew this were the realization of G. Similarly, the judge will choose to sentence a convict for whom $G = 0$ to probation provided $(c+h(n))s > D+\phi\lambda$. For both to hold, we need $P > c+h(n) - \frac{D+\phi\lambda}{s} > 0$. If this occurs, the extensive form becomes



The judge's expected welfare based on their possible sentences are

$$E(W_J)_{Prison} = D + sP - (c+h(n))(s+\theta q(\psi,x)z) + (1-\theta)(1-s)P + \phi\lambda \tag{5}$$

$$E(W_J)_{Probation} = (1-\theta)P - \theta(c+h(n))q(\psi,x)z \tag{6}$$

The judge will therefore choose a prison sentence if $E(W_J)_{Prison} > E(W_J)_{Probation}$, which occurs when

$$\theta > \frac{(c + h(n))s - D - \phi\lambda}{sP} \tag{7}$$

The threshold probability of type $G = G_H$ is $\hat{\theta} \equiv \frac{(c+h(n))s-D-\phi\lambda}{sP}$. Taking the derivative with respect to n:

$$\frac{\partial\hat{\theta}}{\partial n} = \frac{1}{sP}\left(\frac{\partial h}{\partial n} - \phi\frac{\partial\lambda}{\partial n}\right) \tag{8}$$

From equation (4):

$$\frac{\partial\hat{\theta}}{\partial n} = \frac{1}{sP}\left(\frac{\partial h}{\partial n} - \phi p\frac{\partial f(n,s)}{\partial n}\right) \tag{9}$$

This value is negative for either a sufficiently lobbying-susceptible judge or a sufficiently small value for $\frac{\partial h}{\partial n}$, meaning private prison lobbying would likely increase incarceration likelihood if the judge places positive weight on their personal welfare. If we instead assume a non-susceptible judge such that $\phi = 0$, the derivative will always be positive, decreasing incarceration likelihood. More generally,

$$\frac{\partial^2\hat{\theta}}{\partial n\partial\phi} = -p\frac{\partial f(n,s)}{\partial n} < 0 \tag{10}$$

implying increased lobbying susceptibility lowers the judge's incarceration belief threshold for increasing numbers of private prisons.

2.3.3 Optimal Prison Sentence Length

If the judge can choose s when delivering a prison sentence, they will choose s to maximize equation (5). Their choice is independent of the decision whether or not to hand a prison sentence down in the first place. They solve

$$\max_s D + sP - (c + h(n))(s + \theta q(\psi, x)z) + (1-\theta)(1-s)P + \phi\lambda \tag{11}$$

which has first-order condition

$$\theta P - (c + h(n)) + \phi\frac{\partial\lambda}{\partial s} = 0 \tag{12}$$

Substituting in equation (3) gives

$$\theta P - (c + h(n)) + \phi\left(p\frac{\partial f(n,s)}{\partial s} + (c - c_L)\right) = 0 \tag{13}$$

By the implicit function theorem,

$$\frac{\partial s^*}{\partial n} = \phi p \frac{\partial^2 f}{\partial s \partial n} - \frac{\partial h}{\partial n} \tag{14}$$

and

$$\frac{\partial^2 s^*}{\partial n \partial \phi} = p \frac{\partial^2 f}{\partial s \partial n} > 0 \tag{15}$$

which suggest sentencing length decisions follow similar dynamics under lobbying-susceptibility as does the prison-probation decision.

2.3.4 Alternative Assumptions

First, assume $D + sP + \phi\lambda > (c + h(n))s$ holds, but $(c + h(n))s > D + \phi\lambda$ does not. This implies the judge will always choose to send the convict to prison. This will occur when the judge places a very high relative weight on their personal welfare, when the deterrence externality is very high, or when the marginal cost and harm to the convict from incarceration are very small.

Second, consider the case where $G_H \leq (1 - s)w + q(\psi, x)h(n)z$. In this scenario, a type $G = G_H$ convict will choose not to recidivize if given prison, but will still recidivize if given probation. The judge's expected welfare from a prison sentence becomes $D + P - (c + h(n))s + \phi\lambda$ while their expected welfare from a probation sentence remains unchanged. They will choose a prison sentence if

$$\theta > \frac{(c + h(n))s - D - \phi\lambda}{P + (c + h(n))q(\psi, x)z} \tag{16}$$

The derivative of this new threshold with respect to n retains the same general properties as the original case with respect to changes in marginal harm

$$\frac{\partial \hat{\theta}}{\partial n} = \frac{q(\psi, x)z}{(P + (c + h(n))q(\psi, x)z)^2} \left((D + \phi\lambda)\frac{\partial h}{\partial n} - (c + h(n))p\phi \frac{\partial f(n, s)}{\partial n} \right) \tag{17}$$

but the cross-derivative with respect to lobbying susceptibility becomes before complicated:

$$\frac{\partial^2 \hat{\theta}}{\partial n \partial \phi} = \frac{q(\psi, x)z}{(P + (c + h(n))q(\psi, x)z)^2} \left(\lambda \frac{\partial h}{\partial n} - (c + h(n))p \frac{\partial f(n, s)}{\partial n} \right) \tag{18}$$

The sign of the cross-derivative remains negative unless marginal harm is very high or the lobby offer is very high, reflecting diminishing marginal returns from lobbying to prison production.

Next, consider the case where $G_H \leq \min\{(1 - s)w + q(\psi, x)h(n)z, (w + h(n)z)q(\psi, x)\}$. In this scenario, the convict will never choose to recidivize. In this case, the realization of G no longer matters to the payoffs of the judge. The judge will receive $D + P - (c + h(n))s + \phi\lambda$ for a prison sentence and P for a probation sentence. They will choose a prison sentence if $D + \phi\lambda > (c + h(n))s$.

2.4 Theoretical Summary

The theoretical model predicts sentencing behavior will depend on judicial beliefs about the type of gains the convict will receive from recidivism, which relate to whether the convict will commit this secondary crime. A lobby-influenced judge will be more likely to sentence a convict to prison over probation as the number of private prisons within the lobby expands unless the harm to the prisoner is sufficiently great or diminishing returns prevail. A similar dynamic occurs for sentence length.

The expressions in (9) or (12) provide the possible basis for an empirical model, predicting the following functional relationship:

$$\theta = \theta(n, \phi, \psi, x, p) \tag{19}$$

This formulation also allows for conditioning on a particular level ψ or x if so desired.

3 Empirical Model

We can test the hypotheses in the previous section by modeling the probability of a prison sentence with a probit specification:

$$\theta = \Phi(n, \phi, \psi, x, p) \tag{20}$$

where Φ is the cumulative normal density function. The level of lobbying susceptibility, the number of private prisons, and personal demographics are observable or proxiable. While the severity of a crime eludes easy objective measurement, it can be accounted for instead by partitioning by the type of crime committed or by the use of indicator variables for the crime type.

In particular, we specify the following baseline panel data model for a convict i's prison sentence likelihood for a given crime type ψ within a given year t and given state s

$$\theta = \Phi_{i,s,t}(\beta_0 + \beta_1 n_{s,t} + \beta_2 n_{s,t}\phi_{s,t} + \beta_3\phi_{s,t} + \beta_4 x + \beta_5 p + \xi_s + \gamma_t + \varepsilon_{i,s,t}|\psi) \tag{21}$$

where ξ_s are state-level fixed effects, γ_t are yearly fixed effects, and $\varepsilon_{i,\Psi,s,t}$ is the residual error. Any effect of private prisons on the incarceration likelihood will be reflected in the coefficient estimates of β_1, which identifies the type of relationship between the number of private prisons and the incarceration likelihood when corruption is not present, and β_2, which determines the direction of any additional relationship which occurs when corruption is present. To identify the magnitude of these relationships, the marginal effect of private prisons can be found from

$$\frac{\partial \Phi_{i,s,t}}{\partial n_{s,t}} = (\beta_1 + \beta_2 \phi_{s,t})\, \bar{\Phi}'_{i,s,t} \tag{22}$$

where $\bar{\Phi}'_{i,s,t}$ is the conditional mean of marginal normal density function. Potential endogeneity exists between the number of private prisons $n_{s,t}$ and the incarceration likelihood, namely that more private prisons may be built where incarceration likelihoods are naturally higher. This potential bidirectionality necessitates the use of an instrumental variable approach, lest the model be biased and inconsistent.

While a two-stage least squares (2SLS) methodology can be applied to estimating this model and its average marginal effect, its application comes with a number of drawbacks: fitted values can lie outside the zero-to-one interval, efficiency loss in our estimates, increase in bias, and a simple ignorance of information regarding the underlying logistic data-generating process. Neither can a 2SLS-analogue be directly applied to a probit model, even with a linear first stage; as expectation operators are not preserved under nonlinear transformations, orthogonality and thus exogeneity can not be theoretically guaranteed in such a model. One common way to incorporate instrumental variables into a probit model with a continuous endogenous regressor is through the use of a control function estimator (Rivers and Vuong, 1988). For a set of instruments $Z_{s,t}$ which correlate with $n_{s,t}$ but not $\varepsilon_{i,s,t}$, project $n_{s,t}$ onto $Z_{s,t}$:

$$n_{s,t} = \alpha Z_{s,t} + v_{s,t} \tag{23}$$

We can then construct a relationship between $v_{s,t}$ and $\varepsilon_{i,s,t}$ based on the regression correlation coefficient $\rho = \frac{E(v_{s,t}\varepsilon_{i,s,t})}{E(v_{s,t}^2)} \in [-1, 1]$ such that

$$\varepsilon_{i,s,t} = \rho v_{s,t} + e_{i,s,t} \tag{24}$$

After substituting (23) into (21) and using the estimated errors $\hat{v}_{s,t}$ from (24), we can rewrite the control function probit model as

$$\theta = \Phi_{i,s,t}(\beta_0 + \beta_1 n_{s,t} + \beta_2 n_{s,t}\phi_{s,t} + \beta_3 \phi_{s,t} + \beta_4 x + \beta_5 p + \xi_s + \gamma_t + \rho \hat{v}_{s,t} + e_{i,s,t} | \psi) \tag{25}$$

By construction, no endogenous relationship exists between $n_{s,t}$ and $e_{i,s,t}$, allowing equation (25) to be estimated in a straightforward manner, although standard error estimates must be bootstrapped. Marginal effects can be derived from this procedure, but they must be adjusted as our estimates are no longer consistent with regard to the conditional mean $\bar{\Phi}'_{i,s,t}$ (Skeels and Taylor, 2015).

Identification of a valid instrumental variable for the quantity of private prisons within a state in a given year presents difficulty. The rise of private prisons in the early 1980s, accelerating in the 1990s, was a manifestation of an ideological effort of "neoliberalism," which emphasized trade liberalization, deregulation, and privatization to spur economic growth. The degree to which privatization and "neoliberal" ideologies flourished within a state can be at least partially measured by the nature of the economic literature produced by academics at the time. If these ideologies were more relevant, a larger proportion of literature should be dedicated to its study. Given the long lag time between the inception of a paper and its publication, a measure of the relevant literature should lag the underlying ideological saturation it stems from, meaning that reverse causality would be difficult– such an instrument would be naturally "lagged" by construction; incarceration and prison building decisions within a given year might influence future research, but not contemporaneous publications, implying such a measure might serve as a valid instrument for the number of private prisons.

As an extension, this chapter will also consider whether private prisons impact the length of prison sentences received by convicts who are incarcerated. Given a pool of convicts who are divided between those sentenced to incarceration and those sentenced to probation, we must first model the process of clearing the "hurdle" of receiving a prison sentence and then model the length of the sentence received for those who clear it. The selection process operated by the judge can be modeled though a Heckman two-step correction approach: the initial selection process can be modeled similar to the previous probit model for incarceration likelihood, while the second stage which models sentence length can be estimated through two-stage least squares with bootstrapped standard errors while including the Inverse Mill's Ratio (IMR) derived from the first stage as an instrument. However, per Wooldridge (2002), the initial stage must be modified as a control function approach estimates the IMR estimate inconsistently; this modification rather uses a standard probit model, but excludes all endogenous regressors while including the instrument directly into the probit. This can be expressed as

$$\theta = \Phi_{i,s,t}(\beta_0 + \beta_1 Z_{s,t} + \beta_2 Z_{s,t}\phi_{s,t} + \beta_3 \phi_{s,t} + \beta_4 x + \beta_5 p + \xi_s + \gamma_t + \varepsilon_{i,s,t}|\psi) \tag{26}$$

All models estimated[2] will use standard errors which are clustered by state-year, even when bootstrapped, to account for any heteroskedasticity; yearly and state fixed effects to account for unobservable time- or space-invariant factors, respectively; and a handful of state-level variables which might influence the judge's decisions, either through affecting other unobservable aspects of the convict or affecting

[2]The initial probit estimate of the Heckman two-step model does not require clustered standard errors as heteroskedasticity does not impact the estimates or standard errors derived by the second step and the standard errors of the first step are not of import.

the ideological make-up of the judge and/or shape of their justice function.

4 Data

Our measure of private prisons originates from a 2008 inventory conducted by the advocacy group Human Rights Defense Center. The definition of private prisons employed casts a wide net, including prisons, jails, detention centers, juvenile and womens facilities, halfway houses, boot camps, and contractors under immigration enforcement. While the average state had 4.02 such institutions in a given year, the average convict in our dataset existed in a state-year with 14.82 privately-owned incarceration facilities. Texas saw the largest proliferation of private prisons, peaking at 71 institutions in 2008, although Alaska had the most per capita. Twelve states during the sample time period did not have a single private prison, though most subsequently contracted some prison services to a private company. The mean private prison had an occupancy limit of 554 beds.

Our instrument for private prisons, privatization ideology influence, can not be directly measured and is proxied by academic literature on privatization. The measure of literature comes from EconLit publications matching a search for "privatization" or "neoliberalism" based on the state of the author-affiliated institution. This number is weighted by the number of economists per capita within the given state-year as reported by Research Papers in Economics Project (RePEc) to capture both the influence within economics as a discipline and its larger influence on the political climate of a state-year. Relevant papers per per-capita economists averages 0.815 in a given state-year, peaking at 7.105 in Florida in 2000. A cumulative measure is also used, averaging 7.965 and peaking at 81.705 in Florida in 2008. Cumulative papers acts as a leading indicator for private prison construction since 1990, as shown in Figure 1.

Using federal corruption convictions as a proxy for public official lobbying susceptibility sees wide use in the empirical literature (Adsera et al., 2003; Alt and Lassen, 2014; Glaeser and Saks, 2006; Liu and Mikesell, 2014; Meier and Holbrook, 1992; Zuo and Schieffer, 2013). Our measure comes from the number of public officials convicted in violation of federal corruption laws per capita as reported by the Public Integrity Section of the Department of Justice. The most "corrupt" state in our sample is North Dakota at an average of 0.846 corruption convictions per 100,000 people per year, while Oregon sees the fewest such convictions at 0.086 per 100,000 people per year. The average corruption level declined in the first few years to a minimum in 2002 at 0.284 before climbing to a maximum of 0.3725 in 2008. Individual states exhibit wide latitude in a given year; twenty state-years had greater than

1.0 corruption convictions per 100,000–four were greater than 2.0–peaking in 2000 Alaska at 2.579 convictions per 100,000 residents.

The United States Sentencing Commission (USSC) compiles individual-level data on federal criminal trials. Their data includes the type of crime committed by the defendant, whether they were found guilty, the nature of their sentence if convicted (prison or probation and sentence length), and selected personal demographics of the defendant. A number of different demographic attributes were provided, including age, sex, race and ethnicity, education level, citizenship status, and criminal history status. Defendants are classified into six broad categories of crime type, each with associated sub-categories: violent crimes such as murder, sexual misconduct, and assault; property crimes including burglary, arson, and fraud; drug crimes; public order crimes including prostitution, perjury, public intoxication, and regulatory violations; non-violent weapons crimes such as trafficking, illegal manufacture, and registration violations; and immigration crimes.

The USSC data begins in 1993 and continues through the end of the private prison sample in 2008, though coverage for some variables is incomplete in the early years; most notable is the criminal history variable, which only begins partially in 1996 and fully in 1997. Other less complete variables include number of dependents, education variables, and Democratic Party proportion due to cases like the non-partisan Nebraska legislature. Corruption conviction statistics are also missing for two state-years in New Mexico. The full 1993-2008 sample covers nearly a million individual cases in every state, though missing or partial data brings the usable sample down to about 600,000 observations from 1997 to 2008. Table 1 displays summary statistics for each variable. Additional state-level variable data is drawn from the United States Census Bureau and the Bureau of Economic Analysis.

Across the dataset, 87.5% of all convictions resulted in a prison sentence while the remnant were given either probation, a fine, or a suspended sentence. This rate rose steadily from 75.9% in 1993 to a peak of 90.9% in 2006. This also varied heavily by crime type: Violent, drug, weapons, and immigration crimes saw between 93.5%-96.7% prison rates, with property crimes much lower at 60.5% and public order crimes the lowest at 54.5%. The overall composition of crimes changed over the sample period: public order, weapons, immigration crimes rose in proportion while violent, property, and drug crimes all steadily fell. The compositional change can not explain the overall rise in the prison sentence proportion.

Mean sentence length received for those who were incarcerated also varied. Overall, the average sentence was 51.8 months, a figure which declined from a high in 1996 of 60.9 months to a low in 2001 of 46.6 months before rebounding throughout the 2000s. Mean sentence lengths by crime type formed three clear tiers: immigration, property, and public order crimes saw average lengths between 20.6 and 26.4 months; drug and weapons crimes between 75.2 and 78.0 months; and violent crimes at 94.6 months.

The demographics of the individuals involved in these cases skews heavily from overall national population dynamics. Only 31.9% of cases involved a white convict, while 39.9% involved a Hispanic convict, 25.3% involved a black convict, and 2.3% an Asian convict.[3] This is partially driven by the fact that 19.2% of cases were immigration crimes and 26.4% involved a non-citizen, both of which were almost entirely Hispanic-driven[4]. Drug crimes, which made up 38.3% of cases were also heavily minority-oriented.[5] The vast majority of cases involved men, with women only making up 14.1% of the sample; this number declined constantly over the sample period. The sample also skewed toward less educated individuals: a plurality (38.2%) of convicts never graduated high school while only 5.6% had a college degree. The average age of convicts grew from 32.0 years old in 2001 to 37.7 years old in 2008, perhaps reflecting national aging trends. A full 73.9% of convicts with criminal history data available were repeat offenders, which peaked at 87.5% in 2007.

5 Results

Results using the data and the control function estimator in equation (25), hereafter referred to as an IV-Probit, are presented in Table 2 alongside an equivalent 2SLS estimator, a basic OLS specification, and a standard Probit which does not account for endogeneity. All specifications employ standard errors clustered at the 600 state-years within the dataset to combat any potential heteroskedasticity. Indicator variables for each state and each year also ensure any temporal or spatial fixed effects are accounted for, although their results are not reported. To ensure non-singularity, indicators for weapons crimes, male, white, some college, American citizen, and no criminal history were omitted from the estimation process to be used as bases. Coefficient estimates for the Probit and IV-Probit do not represent marginal effects in Table 2 while the OLS and 2SLS estimates can be interpreted as such.

Across all four specifications, the interaction between the number of private prisons and corruption convictions produced a positive and strongly significant coefficient, meaning that as corruption levels increase, increasing the number of private prisons will increase the likelihood of an individual being sentenced to prison. The models differ significantly in the impact of private prisons in the absence of

[3] Only Hawaii saw a notable number of Asian convicts. A majority (53.5%) in the island-state were Asian while no other state crossed 10%.

[4] 83.4% of immigration cases and 84.6% of cases involving a non-citizen featured a Hispanic convict.

[5] 72.6% of drug crimes involved a non-white convict.

corruption, however; when endogeneity is not accounted for, no significant impact can be inferred, but when we instrument for private prisons, a significant negative coefficient is returned. Such a coefficient would be consistent with the theory presented in Section 2 if we assume that the additional harm of attending a private prison outweighs the addition gain in social welfare from the cost reduction of a private prison in the mind of judges.

Outside of these variables of interest, all four models generate highly consistent estimates for each individual-level variable. The specifications suggest violent and drug crimes receive the harshest sentencing decisions while public order and property crimes see the lightest, as born out by previous analysis in the Data Section. Women see a significant reduction in prison likelihood over males, while Hispanics have the highest likelihood followed by blacks with Asians lower than whites. College graduates see slightly higher prison likelihoods than high school graduates, but the likelihood for those who have not graduating high school dwarfs both. In general, the state-level variables do not see significant coefficients.

The estimates for the 2SLS specification also shows the Cragg-Donald F statistic, the test statistic for the Stock-Yogo instrument strength test. Given the large value of this statistic, the instrument of academic papers seems strong, with the 2SLS specification producing far less than 10% of the bias of OLS. However, this test statistic may be artificially inflated as it compares two state-level variables in an individual-level model, producing many repeated observations. Fortunately, Galinato and Rohla (2017) establish the strength of this instrument without this problem of sample repetition. Further information on the first stage estimates predicting private prisons and its interaction with corruption from cumulative academic papers per per-capita economist can be found in Table 3. The coefficient estimates behave as one would like, with highly significant and positive coefficients for the relevant instruments.

Tables 4 through 7 break down the second stage IV-Probit results from Table 2 based on a number of factors and demographics. Table 4 looks at the results when only certain crime types are considered, Table 5 only certain races, Table 6 only certain education levels, and Table 7 considers sex, citizenship status, and criminal history. Positive and statistically significant estimates for the interaction of private prisons and corruption appear for property, drug, and public order crimes but not for violent and immigration crimes; for blacks but not other races; for high school graduates and college graduates, but not those with less than a high school education; for both men and women; for both those with and without criminal history; and for citizens but not non-citizens. At no time is the interaction both statistically significant and negative. These findings broadly support those of Galinato and Rohla

(2017) concerning the confluence of corruption and private prisons.

Table 8 displays the total marginal effect on the extensive likelihood of receiving a prison sentence for both the 2SLS model and the IV-Probit by crime type and demographics. For each specification, the marginal effect at three different levels of corruption convictions is presented: at zero, at the mean value, and at the sample maximum corruption convictions level. Figure 2 presents these IV-Probit marginal effects estimates in graphical form. The two specifications broadly tell the same story: Without corruption, an additional private prison *lowers* the likelihood of a prison sentence overall and especially for drug crimes, men, blacks, those with criminal history, and those with less than a high school diploma; these may be viewed as the groups traditionally "overrepresented" in the prison system relative the national demographics. When corruption sits at mean levels across our sample, very little statistically significant marginal effect can be isolated and, with the exception of public order crimes, tends to still be negative in impact.

However, when corruption climbs higher, a number of marginal effects become positive and statistically significant overall and most prominently for women, public order crimes, high school and college graduates, American citizens, and those without criminal history[6]–all groups traditionally "underrepresented" in the American prison system. Each additional private prison in a highly-corrupt state[7] increases prison likelihood for an individual prisoner by 0.44%, and by as much as 2.2% for a public order crime, 1.3% for a female convict, 1.0% for a college graduate, or 0.9% for a high school graduate. While this probabilities seem individually small, the rapid growth of private prisons means compounding occurs; multiple private prisons being constructed within a given state in a given year occurs frequently in the dataset. Conversely, in a corruption-free state, an additional private prison reduces overall prison likelihood by 0.11%, a much smaller amount than its opposite in a highly corrupt state.

Table 8 also suggests a structural break may have occurred around the year 2001. Prior to this year, no statistically significant marginal effect occurs when corruption is zero, but a positive marginal effect can be identified past a threshold level of corruption. After this year, the effect switches such that the marginal effect is statistically significant and negative at low levels of corruption and relatively smaller at higher levels. Several notable events occurred around 2001: first, the Department of Justice issued

[6]The marginal effects on males and on those with a criminal history show the largest latitude of any of the estimates, where a low corruption environment pushes them out of prison while a higher corruption environment pushes them in, the only groups for which this occurs. This likely occurs as both groups make up very large proportions of the overall sample and, as these are often seen as the "default" offender profile, the judge may not weigh their utility to the extent they might in a more "abnormal"–thus higher profile–case.

[7]Here, a highly-corrupt state refers to the highest observed corruption level in the dataset, namely Alaska in 2000. However, there is no realistic upper constraint on the amount of corruption convictions per capita in a given state-year, meaning the marginal effects listed here could theoretically be even larger.

a prominent report on rising issues with private prisons (Austin and Coventry, 2001) while a Louisiana moratorium and a major scandal involving an Arizonan private prison run by drug cartels led to increased media attention; second, the growth rate in the number of private prisons rapidly decelerated as demonstrated in Figure 1; and third, increased focus on immigration and border enforcement in the wake of the September 11, 2001 attacks led to larger federal contracts with private prisons firms, providing a financial boost while lessening the immediate need to directly engage in potentially risky lobby schemes.[8]

Table 10 uses the number of private prison beds as a measure of capacity and demand by private prisons as a robustness check. Results are displayed for the IV-Probit specification for both the overall change in incarceration likelihood and a breakdown by crime type. Coefficient signs are highly similar to estimates generated using the total number of facilities, though they are not as statistically significant as before. The interaction term is only significant at the $p < 0.1$ level for drug crimes and public order crimes.

Results for the Heckman estimates of intensive margin effects were generally statistically insignificant as shown in Table 9. Estimates are based on one thousand bootstrap replications per Wooldridge (2002). Each row represents an individual regression specification for each category of individual. The columns represent the coefficient estimates for the independent variables of interest: the raw number of private prisons, its interaction with corruption convictions, and the IMR to denote whether significant selection effects are present.

For only one demographic subgroup were the bootstrapped coefficient estimates of interest statistically significant, namely for those with a previous criminal history[9], for whom the interaction of corruption and private prisons increased their sentence length. A convict with a criminal history would receive a additional 56 days in prison for each additional private prison in a highly corrupt state compared to a low-corruption state. While not statistically significant, the coefficient estimates for the interaction term among other demographics or crime types were generally positive. This lack of statistical significance should not be overly surprising given the noisiness of sentence lengths, their reliance on legal heuristics and unobservable individual-level factors, the wide variety of crime subtypes in each crime type, and the aggressive bootstrapping necessary to generate proper standard errors which rapidly strips non-individual level coefficients of significance. Simply put, the data available is generally not

[8]While not included here, the data shows some limited evidence that the pre-2001 dynamic may have returned during 2007-08 as the U.S. economy began its downturn, leading some governments to cut funding for private prisons, increasing the incentive to engage in the lobby market.

[9]This was also the only category which showed strongly statistically significant (i.e. $p < 0.05$) levels of selection as evidenced by a significant coefficient for the Inverse Mill's Ratio. College graduates and drug crimes also had statistically significant selection issues, but only at the $p < 0.1$ level.

sufficiently detailed to identify relationships in this case.

6 Next Steps

Additional robustness checks could be performed. For example, a conditional or nested logit by crime type or by demographic characteristic might supplement results for the partitioned regressions. Further work should be undertaken on the sentence length regressions, especially given how the current bootstrapping procedure appears to be the cause of the near-complete lack of statistical significance to the estimates. Ideally, more recent data could also be collected on the number of private prisons per state after 2008. This may not be possible, however.

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Table 1: **Summary Statistics, 1993-2008**

Variable	N	Mean	Std. Dev.	Min.	Max.
Individual-Level Variables					
Received an Incarceration Sentence	940,793	0.8754	0.3303	0	1
Length of Incarceration Sentence *(in months)*	940,793	51.8029	91.0996	0	11520
Violent Crime Type	946,294	0.0427	0.2021	0	1
Property Crime	946,294	0.2286	0.4199	0	1
Drug Crime	946,294	0.3825	0.4860	0	1
Public Order Crime	946,294	0.0623	0.2416	0	1
Weapons Crime	946,294	0.0766	0.2659	0	1
Immigration Crime	946,294	0.1919	0.3938	0	1
Age *(in years)*	927,487	34.5408	10.7927	16	103
Female	932,243	0.1411	0.3482	0	1
White	912,209	0.3187	0.4660	0	1
Black	912,209	0.2532	0.4349	0	1
Hispanic	883,012	0.3992	0.4897	0	1
Asian	912,209	0.0232	0.1505	0	1
Less than High School	876,151	0.3817	0.4858	0	1
High School Graduate	876,151	0.2496	0.4323	0	1
Some College	876,151	0.1385	0.3454	0	1
College Graduate	876,151	0.0556	0.2291	0	1
American Citizen	915,783	0.6576	0.4745	0	1
Not an American Citizen	915,783	0.2635	0.4405	0	1
Has Criminal History	750,183	0.7387	0.4394	0	1
Number of Dependents	875,350	3.2711	12.8689	0	99
State-Level Variables					
Number of Private Prisons	926,118	14.8181	20.0651	0	71
Number of Private Prison Beds *(in thousands)*	926,118	8.4512	11.4219	0	41.51
Corruption Convictions Per Capita *(per 100,000)*	926,118	0.3246	0.2107	0	2.5479
Cumulative Papers per Economist Per Capita	926,118	22.1446	21.8720	0	81.7052
State Price Index *(base 2008)*	926,118	84.9743	9.5593	56.049	118.220
Real Median Household Income	808,755	37025.34	49034.51	24514.74	59285.31
Democratic Party Proportion in Legislature	761,471	0.4927	0.1170	0.1143	0.8889
In-State Federal Prisons	808,755	4.8244	4.0121	0	12

Table 2: **Incarceration Likelihood Results for All Crimes, 1997-2008**

Dep. Var.: Given Prison Sentence	OLS	2SLS	Probit	IV-Probit
Number of Private Prisons	-0.0003	-0.0017	0.0023	-0.0087
	(0.0002)	(0.0006)***	(0.0021)	(0.0045)*
Private Prisons x Corruption	0.0013	0.0023	0.0108	0.0168
	(0.0004)***	(0.0007)***	(0.0038)***	(0.0057)***
Corruption Convictions Per Capita	-0.0057	-0.0125	-0.0294	-0.0666
	(0.0053)	(0.0056)**	(0.0373)	(0.0374)*
Individual-Level Variables				
Violent Crime Type	0.0222	0.0226	0.2005	0.2041
	(0.0021)***	(0.0021)***	(0.0250)***	(0.0250)***
Property Crime	-0.1229	-0.1226	-0.6852	-0.6827
	(0.0028)***	(0.0028)***	(0.0171)***	(0.0170)***
Drug Crime	0.0155	0.0157	0.1384	0.1398
	(0.0014)***	(0.0014)***	(0.0178)***	(0.0178)***
Public Order Crime	-0.1411	-0.1410	-0.7747	-0.7733
	(0.0037)***	(0.0037)***	(0.0184)***	(0.0184)***
Immigration Crime	-0.0403	-0.0396	-0.3256	-0.3200
	(0.0030)***	(0.0030)***	(0.0328)***	(0.0332)***
Age	-0.0000	-0.0000	0.0006	0.0006
	(0.0001)	(0.0001)	(0.0003)*	(0.0003)*
Female	-0.0858	-0.0857	-0.4560	-0.4551
	(0.0028)***	(0.0028)***	(0.0091)***	(0.0090)***
Black	0.0141	0.0141	0.1282	0.1279
	(0.0016)***	(0.0016)***	(0.0106)***	(0.0106)***
Hispanic	0.0286	0.0286	0.2400	0.2403
	(0.0017)***	(0.0017)***	(0.0125)***	(0.0125)***
Asian	-0.0113	-0.0114	-0.0388	-0.0394
	(0.0050)**	(0.0050)**	(0.0223)*	(0.0223)*
Less than High School	0.0202	0.0203	0.1809	0.1813
	(0.0017)***	(0.0017)***	(0.0106)***	(0.0106)***
High School Graduate	0.0063	0.0063	0.0367	0.0371
	(0.0016)***	(0.0016)***	(0.0086)***	(0.0086)***
College Graduate	0.0077	0.0077	0.0607	0.0605
	(0.0025)***	(0.0025)***	(0.0112)***	(0.0112)***
Not an American Citizen	0.0466	0.0466	0.5528	0.5516
	(0.0026)***	(0.0026)***	(0.0268)***	(0.0269)***
Has Criminal History	0.0713	0.0714	0.4342	0.4345
	(0.0022)***	(0.0022)***	(0.0073)***	(0.0073)***
Number of Dependents	0.0001	0.0001	0.0024	0.0024
	(0.0001)	(0.0001)	(0.0013)*	(0.0013)*
State-Level Variables				
State Price Index	-0.0004	0.0003	-0.0052	0.0004
	(0.0004)	(0.0006)	(0.0033)	(0.0045)
Real Median Household Income	-0.0001	-0.0002	-0.0009	-0.0017
	(0.0001)	(0.0001)	(0.0007)	(0.0009)*
Democratic Prop. In Legislature	-0.0084	-0.0181	-0.1007	-0.1641
	(0.0168)	(0.0187)	(0.1277)	(0.1377)
In-State Federal Prisons	0.0005	0.0017	0.0108	0.0201
	(0.0013)	(0.0017)	(0.0100)	(0.0130)
R^2	0.1273	0.1272	0.2029	
Cragg-Donald F-statistic		51,830		

N=579,641. All estimates include state and yearly fixed effects.
Clustered standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: **First-Stage Results Predicting Private Prisons, 1997-2008**

Dependent Variable:	Private Prisons	Priv. Prisons x Corruption
Cumulative Papers per Per-Capita Economist	0.2399	-0.0672
	(0.0625)***	(0.0259)***
Papers x Corruption Convictions	0.1191	0.4212
	(0.0859)	(0.0536)***
Corruption Convictions Per Capita	-0.1564	1.5320
	(0.7727)	(0.5843)***
Individual-Level Variables		
Violent Crime Type	0.2380	0.0576
	(0.0516)***	(0.0215)***
Property Crime	0.0938	0.0328
	(0.0361)***	(0.0149)**
Drug Crime	0.0445	0.0173
	(0.0352)	(0.0157)
Public Order Crime	-0.0036	0.0082
	(0.0355)	(0.0153)
Immigration Crime	0.3679	0.1155
	(0.0601)***	(0.0298)***
Age	-0.0006	-0.0003
	(0.0006)	(0.0002)
Female	0.0861	0.0185
	(0.0170)***	(0.0076)**
Black	-0.0326	-0.0086
	(0.0231)	(0.0096)
Hispanic	0.0208	0.0116
	(0.0234)	(0.0079)
Asian	-0.0601	-0.0304
	(0.0536)	(0.0207)
Less than High School	0.0330	0.0076
	(0.0217)	(0.0073)
High School Graduate	0.0245	0.0080
	(0.0184)	(0.0069)
College Graduate	-0.0078	-0.0120
	(0.0189)	(0.0080)
Not an American Citizen	-0.0567	-0.0244
	(0.0283)**	(0.0130)*
Has Criminal History	0.0601	0.0314
	(0.0188)***	(0.0075)***
Number of Dependents	0.0044	-0.0010
	(0.0107)	(0.0030)
State-Level Variables		
State Price Index	0.4841	0.0869
	(0.1309)***	(0.0422)**
Real Median Household Income	-0.1023	-0.0225
	(0.0208)***	(0.0083)***
Democratic Prop. In Legislature	-2.8091	-1.4784
	(4.0606)	(1.6169)
In-State Federal Prisons	-0.5593	0.1028
	(0.8168)	(0.3460)

Note: First-stage results are identical for 2SLS and IV-Probit specifications.

Table 4: **IV-Probit Incarceration Likelihood Results by Crime Type, 1997-2008**

Dep. Var.: Given Prison Sentence	Violent	Property	Drug	Pub. Order	Immig.
Number of Private Prisons	-0.0927	0.0004	-0.0324	0.0088	-0.0206
	(0.0491)*	(0.0072)	(0.0140)**	(0.0111)	(0.0164)
Private Prisons x Corruption	-0.0196	0.0111	0.0191	0.0313	0.0141
	(0.0305)	(0.0067)*	(0.0115)*	(0.0150)**	(0.0139)
Corruption Convictions Per Capita	0.1694	-0.0960	0.0051	-0.2024	0.1722
	(0.1586)	(0.0478)**	(0.0877)	(0.0945)**	(0.1666)
Individual-Level Variables					
Age	-0.0092	0.0029	0.0037	-0.0051	0.0016
	(0.0017)***	(0.0005)***	(0.0008)***	(0.0008)***	(0.0012)
Female	-0.5808	-0.3514	-0.4522	-0.5671	-0.4809
	(0.0501)***	(0.0121)***	(0.0165)***	(0.0220)***	(0.0255)***
Black	0.2447	-0.0460	0.4446	0.0014	0.0148
	(0.0444)***	(0.0141)***	(0.0214)***	(0.0262)	(0.0493)
Hispanic	-0.0232	0.0536	0.5020	0.1375	0.2788
	(0.0711)	(0.0206)***	(0.0242)***	(0.0293)***	(0.0347)***
Asian	0.1002	0.0056	0.1956	-0.3272	-0.0321
	(0.1335)	(0.0280)	(0.0522)***	(0.0502)***	(0.0647)
Less than High School	0.2799	0.0280	0.3302	0.1054	0.3296
	(0.0497)***	(0.0151)*	(0.0163)***	(0.0257)***	(0.0361)***
High School Graduate	0.1106	-0.0413	0.1673	-0.0053	0.1707
	(0.0403)***	(0.0118)***	(0.0156)***	(0.0214)	(0.0342)***
College Graduate	-0.1548	0.0699	-0.1509	0.0121	-0.0938
	(0.0751)**	(0.0140)***	(0.0291)***	(0.0262)	(0.0546)*
Not an American Citizen	0.5751	0.3735	0.7531	0.3789	0.6143
	(0.1402)***	(0.0332)***	(0.0433)***	(0.0476)***	(0.0422)***
Has Criminal History	0.5845	0.4500	0.3176	0.4476	0.6268
	(0.0411)***	(0.0107)***	(0.0145)***	(0.0185)***	(0.0274)***
Number of Dependents	-0.0005	-0.0017	0.0108	-0.0047	0.0052
	(0.0031)	(0.0016)	(0.0068)	(0.0029)	(0.0011)***
State-Level Variables					
State Price Index	0.0356	-0.0068	0.0125	-0.0029	0.0220
	(0.0192)*	(0.0049)	(0.0110)	(0.0060)	(0.0160)
Real Median Household Income	-0.0033	-0.0003	-0.0054	-0.0001	-0.0017
	(0.0033)	(0.0008)	(0.0018)***	(0.0015)	(0.0039)
Democratic Prop. In Legislature	-0.7366	-0.2138	-0.1269	0.7240	-0.8342
	(0.5676)	(0.1599)	(0.2770)	(0.2647)***	(0.5008)*
In-State Federal Prisons	0.0611	-0.0159	0.0301	-0.0073	0.0285
	(0.0850)	(0.0131)	(0.0403)	(0.0409)	(0.0334)
N	23,449	122,739	234,557	35,154	107,218

All estimates include state and yearly fixed effects.

Clustered standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: **IV-Probit Incarceration Likelihood Results by Race, 1997-2008**

Dep. Var.: Given Prison Sentence	White	Black	Hispanic	Asian
Number of Private Prisons	-0.0059	-0.0171	-0.0261	-0.0975
	(0.0069)	(0.0090)*	(0.0150)*	(0.0680)
Private Prisons x Corruption	0.0104	0.0249	0.0092	-0.0264
	(0.0071)	(0.0092)***	(0.0098)	(0.0403)
Corruption Convictions Per Capita	-0.0733	-0.1272	0.3000	-0.1024
	(0.0447)	(0.0713)*	(0.1200)**	(0.1733)
Individual-Level Variables				
Violent Crime Type	0.2896	0.1781	0.0017	0.1964
	(0.0315)***	(0.0474)***	(0.0701)	(0.1747)
Property Crime	-0.4705	-0.9331	-0.8078	-0.6734
	(0.0216)***	(0.0316)***	(0.0418)***	(0.1193)***
Drug Crime	0.0979	0.0804	0.3244	0.2022
	(0.0243)***	(0.0300)***	(0.0414)***	(0.1202)*
Public Order Crime	-0.5905	-1.0281	-0.8006	-1.0846
	(0.0240)***	(0.0369)***	(0.0427)***	(0.1245)***
Immigration Crime	-0.1944	-0.8384	-0.2358	-0.5975
	(0.0493)***	(0.0620)***	(0.0460)***	(0.1247)***
Age	0.0009	-0.0020	0.0017	0.0010
	(0.0004)**	(0.0007)***	(0.0006)***	(0.0020)
Female	-0.3475	-0.5183	-0.4979	-0.4082
	(0.0110)***	(0.0172)***	(0.0144)***	(0.0430)***
Less than High School	0.1092	0.1622	0.2444	0.2390
	(0.0138)***	(0.0176)***	(0.0214)***	(0.0436)***
High School Graduate	0.0195	0.0267	0.0839	0.0414
	(0.0117)*	(0.0154)*	(0.0208)***	(0.0431)
College Graduate	0.0079	0.1660	0.0943	-0.0182
	(0.0126)	(0.0281)***	(0.0354)***	(0.0485)
Not an American Citizen	0.3332	0.5340	0.5944	0.3549
	(0.0312)***	(0.0418)***	(0.0331)***	(0.0540)***
Has Criminal History	0.4088	0.5886	0.3994	0.4140
	(0.0100)***	(0.0148)***	(0.0154)***	(0.0339)***
Number of Dependents	-0.0013	0.0091	0.0053	-0.0027
	(0.0012)	(0.0055)*	(0.0007)***	(0.0033)
State-Level Variables				
State Price Index	-0.0015	-0.0009	0.0127	0.0057
	(0.0045)	(0.0058)	(0.0139)	(0.0167)
Real Median Household Income	-0.0014	0.0002	-0.0060	-0.0100
	(0.0009)	(0.0011)	(0.0027)**	(0.0037)***
Democratic Prop. In Legislature	-0.2076	0.0456	-0.8184	-0.0303
	(0.1382)	(0.2049)	(0.3645)**	(0.7335)
In-State Federal Prisons	0.0156	0.0188	0.0162	-0.0527
	(0.0148)	(0.0211)	(0.0313)	(0.0538)
N	178,381	149,991	230,278	11,106

All estimates include state and yearly fixed effects.

Clustered standard errors in parentheses: *** p <0.01, ** p <0.05, * p <0.1

Table 6: **IV-Probit Incarceration Likelihood Results by Education, 1997-2008**

Dep. Var.: Given Prison Sentence	Less than HS	HS Graduate	College Graduate
Number of Private Prisons	-0.0107	-0.0099	0.0029
	(0.0059)*	(0.0063)	(0.0102)
Private Prisons x Corruption	0.0110	0.0302	0.0178
	(0.0074)	(0.0091)***	(0.0105)*
Corruption Convictions Per Capita	0.0465	-0.1691	-0.1350
	(0.0605)	(0.0480)***	(0.0846)
Individual-Level Variables			
Violent Crime Type	0.2356	0.2212	0.2881
	(0.0410)***	(0.0343)***	(0.0893)***
Property Crime	-0.8176	-0.7352	-0.1655
	(0.0273)***	(0.0213)***	(0.0592)***
Drug Crime	0.1948	0.1275	0.2962
	(0.0263)***	(0.0221)***	(0.0625)***
Public Order Crime	-0.8327	-0.8009	-0.3525
	(0.0289)***	(0.0245)***	(0.0631)***
Immigration Crime	-0.3140	-0.3529	-0.2514
	(0.0406)***	(0.0374)***	(0.0764)***
Age	-0.0035	0.0008	0.0026
	(0.0005)***	(0.0005)	(0.0009)***
Female	-0.5528	-0.4178	-0.3439
	(0.0151)***	(0.0135)***	(0.0221)***
Black	0.2289	0.1225	0.1031
	(0.0177)***	(0.0152)***	(0.0255)***
Hispanic	0.2694	0.2286	0.2835
	(0.0190)***	(0.0166)***	(0.0349)***
Asian	0.0815	0.0014	-0.0848
	(0.0462)*	(0.0391)	(0.0402)**
Not an American Citizen	0.5843	0.5404	0.3525
	(0.0323)***	(0.0323)***	(0.0403)***
Has Criminal History	0.4637	0.4929	0.3051
	(0.0135)***	(0.0124)***	(0.0180)***
Number of Dependents	0.0031	0.0010	0.0025
	(0.0013)**	(0.0014)	(0.0029)
State-Level Variables			
State Price Index	0.0019	-0.0025	-0.0025
	(0.0065)	(0.0055)	(0.0079)
Real Median Household Income	-0.0026	-0.0016	-0.0016
	(0.0012)**	(0.0011)	(0.0013)
Democratic Prop. In Legislature	-0.2802	-0.0213	-0.2654
	(0.1942)	(0.1788)	(0.2164)
In-State Federal Prisons	0.0200	0.0200	0.0147
	(0.0227)	(0.0166)	(0.0212)
N	273,537	176,107	34,035

All estimates include state and yearly fixed effects.

Clustered standard errors in parentheses: *** p <0.01, ** p <0.05, * p <0.1

Table 7: **IV-Probit Likelihood Results, Other Demographics, 1997-2008**

DV: Given Prison Sentence	Male	Female	Crim. Hist.	No C.H.	Citizen	Non-Citizen
No. of Private Prisons	-0.0093	-0.0083	-0.0118	-0.0038	-0.0051	-0.0349
	(0.0048)*	(0.0067)	(0.0050)**	(0.0064)	(0.0048)	(0.0198)*
Private Prisons x Corrupt.	0.0151	0.0220	0.0181	0.0143	0.0144	0.0209
	(0.0062)**	(0.0080)***	(0.0070)***	(0.0085)*	(0.0062)**	(0.0136)
Corruption Conv. Per Cap.	-0.0406	-0.1377	-0.0873	-0.0314	-0.0790	0.2225
	(0.0386)	(0.0581)**	(0.0449)*	(0.0634)	(0.0374)**	(0.1592)
Individual-Level Variables						
Violent Crime Type	0.2172	0.3505	0.2099	0.3966	0.2248	0.1217
	(0.0257)***	(0.0595)***	(0.0281)***	(0.0479)***	(0.0265)***	(0.1587)
Property Crime	-0.7101	-0.3880	-0.7338	-0.3621	-0.6814	-0.7526
	(0.0173)***	(0.0430)***	(0.0194)***	(0.0296)***	(0.0179)***	(0.0769)***
Drug Crime	0.1145	0.4273	0.0538	0.5427	0.0863	0.5390
	(0.0185)***	(0.0421)***	(0.0188)***	(0.0325)***	(0.0182)***	(0.0828)***
Public Order Crime	-0.7390	-0.6422	-0.7937	-0.4888	-0.7568	-0.8518
	(0.0190)***	(0.0445)***	(0.0207)***	(0.0326)***	(0.0193)***	(0.0888)***
Immigration Crime	-0.3420	-0.0693	-0.2340	-0.1646	-0.3336	-0.3124
	(0.0354)***	(0.0526)	(0.0343)***	(0.0469)***	(0.0416)***	(0.0790)***
Age	-0.0006	0.0050	-0.0013	0.0026	0.0000	0.0006
	(0.0004)*	(0.0006)***	(0.0004)***	(0.0005)***	(0.0003)	(0.0011)
Female			-0.4992	-0.3825	-0.4422	-0.5036
			(0.0112)***	(0.0121)***	(0.0099)***	(0.0261)***
Black	0.1925	-0.0402	0.2124	-0.0580	0.1160	0.2118
	(0.0116)***	(0.0167)**	(0.0118)***	(0.0160)***	(0.0110)***	(0.0444)***
Hispanic	0.2717	0.1525	0.2073	0.2431	0.1642	0.3188
	(0.0130)***	(0.0209)***	(0.0149)***	(0.0168)***	(0.0135)***	(0.0399)***
Asian	-0.0209	-0.1199	0.0037	-0.0692	-0.0722	0.0753
	(0.0244)	(0.0426)***	(0.0279)	(0.0293)**	(0.0259)***	(0.0651)
Less than High School	0.2249	0.0650	0.1952	0.1371	0.1558	0.2638
	(0.0114)***	(0.0178)***	(0.0116)***	(0.0164)***	(0.0107)***	(0.0343)***
High School Graduate	0.0525	-0.0090	0.0739	-0.0309	0.0327	0.1340
	(0.0096)***	(0.0150)	(0.0104)***	(0.0133)**	(0.0092)***	(0.0325)***
College Graduate	0.0861	0.0610	-0.0046	0.0709	0.0703	-0.0397
	(0.0129)***	(0.0226)***	(0.0156)	(0.0150)***	(0.0117)***	(0.0442)
Not an American Citizen	0.5472	0.5143	0.5671	0.5150		
	(0.0277)***	(0.0309)***	(0.0300)***	(0.0297)***		
Has Criminal History	0.4512	0.3856			0.4522	0.5593
	(0.0086)***	(0.0120)***			(0.0079)***	(0.0300)***
Number of Dependents	0.0042	-0.0015	0.0028	0.0002	0.0033	0.0032
	(0.0013)***	(0.0022)	(0.0009)***	(0.0025)	(0.0009)***	(0.0011)***
State-Level Variables						
State Price Index	0.0016	-0.0012	0.0032	-0.0041	-0.0023	0.0203
	(0.0043)	(0.0069)	(0.0050)	(0.0061)	(0.0042)	(0.0197)
Real Median H.H. Inc.	-0.0020	-0.0011	-0.0013	-0.0023	-0.0008	-0.0067
	(0.0009)**	(0.0012)	(0.0010)	(0.0011)**	(0.0008)	(0.0033)**
Dem.Prop. In Legis.	-0.1970	-0.0717	-0.1524	-0.1616	-0.1136	-1.0210
	(0.1399)	(0.2043)	(0.1531)	(0.1689)	(0.1353)	(0.4476)**
In-State Federal Prisons	0.0278	0.0028	0.0207	0.0181	0.0158	0.0150
	(0.0146)*	(0.0170)	(0.0166)	(0.0134)	(0.0123)	(0.0417)
N	499,309	80,332	430,565	149,076	388,974	150,630

All estimates include state and yearly fixed effects.
Clustered standard errors in parentheses: *** p <0.01, ** p <0.05, * p <0.1

Table 8: **Marginal Extensive Effect of a Private Prison by Corruption Level**

	2SLS			IV-Probit		
Corruption Level:	0	$\bar{\phi}$	max(ϕ)	0	$\bar{\phi}$	max(ϕ)
Overall	-0.0017	-0.0009	0.0040	-0.0011	-0.0004	0.0044
	(0.0006)***	(0.0006)	(0.0019)**	(0.0004)**	(0.0005)	(0.0012)***
By Crime Type:						
Violent Crime	-0.0064	-0.0068	-0.0099	-0.0065	-0.0070	-0.0101
	(0.0035)*	(0.0037)*	(0.0070)	(0.0031)**	(0.0034)*	(0.0069)
Property Crime	-0.0003	0.0008	0.0081	0.0001	0.0011	0.0082
	(0.0020)	(0.0021)	(0.0052)	(0.0007)	(0.0009)	(0.0048)*
Drug Crime	-0.0023	-0.0019	0.0005	-0.0021	-0.0017	0.0010
	(0.0009)***	(0.0008)**	(0.0017)	(0.0004)***	(0.0006)**	(0.0013)
Public Order Crime	0.0013	0.0040	0.0223	0.0019	0.0045	0.0223
	(0.0030)	(0.0034)	(0.0117)*	(0.0020)	(0.0029)*	(0.104)**
Immigration Crime	-0.0006	-0.0002	0.0022	-0.0038	-0.0030	0.0029
	(0.0012)	(0.0014)	(0.0035)	(0.0025)*	(0.0028)	(0.0041)
For an Individual of Type:						
Male	-0.0015	-0.0009	0.0027	-0.0010	-0.0005	0.0033
	(0.0005)***	(0.0006)*	(0.0017)	(0.0003)***	(0.0006)	(0.0015)**
Female	-0.0022	-0.0004	0.0116	-0.0022	-0.0003	0.0126
	(0.0017)	(0.0018)	(0.0050)**	(0.0017)	(0.0020)	(0.0048)***
White	-0.0012	-0.0004	0.0050	-0.0010	-0.0004	0.0033
	(0.0013)	(0.0013)	(0.0036)	(0.0009)	(0.0010)	(0.0029)
Black	-0.0020	-0.0010	0.0056	-0.0017	-0.0009	0.0046
	(0.0011)*	(0.0011)	(0.0027)**	(0.0012)	(0.0014)	(0.0026)*
Hispanic	-0.0015	-0.0011	0.0012	-0.0031	-0.0028	-0.0003
	(0.0010)	(0.0010)	(0.0019)	(0.0018)*	(0.0021)	(0.0033)
Asian	-0.0129	-0.0157	-0.0347	-0.0133	-0.0145	-0.0225
	(0.0119)	(0.0110)	(0.0160)**	(0.0118)	(0.0125)	(0.0169)
Less than High School	-0.0013	-0.0010	0.0007	-0.0011	-0.0007	0.0018
	(0.0005)**	(0.0005)*	(0.0015)	(0.0004)**	(0.004)*	(0.011)*
High School Graduate	-0.0017	-0.0003	0.0094	-0.0013	0.0000	0.0086
	(0.0009)*	(0.0010)	(0.0033)***	(0.0008)*	(0.0008)	(0.0030)***
College Graduate	0.0002	0.0017	0.0114	0.0006	0.0017	0.0097
	(0.0024)	(0.0017)	(0.0068)*	(0.0027)	(0.0028)	(0.0061)*
American Citizen	-0.0010	-0.0002	0.0053	-0.0008	-0.0001	0.0049
	(0.0007)	(0.0008)	(0.0025)**	(0.0006)	(0.0007)	(0.0025)**
Not an American Citizen	-0.0007	-0.0003	0.0026	-0.0025	-0.0020	0.0013
	(0.0008)	(0.0009)	(0.0022)	(0.0015)*	(0.0016)	(0.0028)
Has Criminal History	-0.0015	-0.0009	0.0031	-0.0011	-0.0006	0.0033
	(0.0005)***	(0.0005)*	(0.0017)*	(0.002)***	(0.0003)**	(0.0013)***
No Criminal History	-0.0024	-0.0013	0.0066	-0.0009	0.0002	0.0077
	(0.0014)*	(0.0015)	(0.0042)	(0.0004)**	(0.0006)	(0.0032)**
By Time Period:						
1997-2001	-0.0041	-0.0031	0.0056	0.0032	0.0034	0.0043
	(0.0057)	(0.0050)	(0.0029)**	(0.0032)	(0.0030)	(0.0021)**
2002-2008	-0.0018	-0.0013	0.0024	-0.0011	-0.0006	0.0027
	(0.0006)***	(0.0006)**	(0.0025)	(0.0006)**	(0.0005)	(0.0015)*

Mean corruption level $\bar{\phi}$ faced: 0.3246. Maximum: 2.5479

Clustered standard errors in parentheses: *** p <0.01, ** p <0.05, * p <0.1

Table 9: **Heckman Sentence Length Results, 1997-2008**

Dep. Var.: Sentence Length (*months*)	Priv. Prisons	Priv. Prisons x Corruption	Inv. Mills
Overall	-0.4748	0.4023	-0.0140
	(1.4030)	(0.5654)	(0.1858)
By Crime Type:			
Violent Crime	-1.3261	-2.0548	4.8757
	(10.7798)	(2.0512)	(11.8900)
Property Crime	0.0820	0.4921	0.0343
	(0.7807)	(0.5362)	(0.0412)
Drug Crime	-0.1916	0.5664	-8.0686
	(1.7743)	(0.9943)	(4.7840)*
Public Order Crime	-1.5394	0.2080	-0.0310
	(2.7897)	(1.5097)	(0.0362)
Immigration Crime	-0.1157	-0.0869	-0.4903
	(5.1460)	(1.3317)	(0.3691)
For an Individual of Type:			
Male	-0.5059	0.4329	-0.2699
	(1.1017)	(0.6087)	(2.1527)
Female	-0.5219	0.3325	-0.0004
	(1.6206)	(0.6210)	(0.0069)
White	-0.0807	0.6736	-0.2062
	(0.7598)	(0.5668)	(0.9413)
Black	-0.1935	0.7479	-0.1950
	(1.5931)	(0.9962)	(0.2327)
Hispanic	-0.1782	-0.4446	-0.0045
	(5.5613)	(2.0701)	(0.0811)
Asian	-4.4266	0.3153	-0.0180
	(108.5076)	(52.4601)	(0.0983)
Less than High School	-0.0036	0.0883	-0.0100
	(0.7007)	(0.4082)	(0.0138)
High School Graduate	-0.5712	0.7277	-0.0997
	(1.3891)	(0.5663)	(0.2011)
College Graduate	0.4685	0.6204	-3.0724
	(2.7486)	(1.4860)	(1.7235)*
American Citizen	-0.1248	0.4881	-0.1727
	(0.6941)	(0.3552)	(0.2957)
Not an American Citizen	0.1963	-0.5549	0.0288
	(1.7382)	(0.7364)	(1.6008)
Has Criminal History	-0.7242	0.7311	-31.0073
	(1.1724)	(0.4072)*	(2.3682)***
No Criminal History	0.4284	-0.0555	0.0092
	(16.4821)	(2.5697)	(0.0172)

Each row is a separate regression. Includes all controls present previously.
All estimates include state and yearly fixed effects.
Clustered standard errors in parentheses: *** p <0.01, ** p <0.05, * p <0.1

Table 10: **IV-Probit Likelihood Results, Number of Private Prison Beds, 1997-2008**

DV: Given Prison Sentence	Overall	Violent	Property	Drug	Pub. Order	Immig.
Private Prison Beds	-0.0015	0.2332	-0.2358	-0.0632	0.0058	-0.2754
	(0.0296)	(0.4942)	(0.2651)	(0.0456)*	(0.0203)	(0.7758)
P.P. Beds x Corrupt.	0.0116	-0.1192	0.0672	0.0352	0.1111	0.0555
	(0.0096)	(0.3004)	(0.0935)	(0.0264)*	(0.0587)*	(0.0878)
Corruption Conv. Per Cap.	-0.0890	0.0052	-0.0791	-0.1520	-0.0789	0.3824
	(0.0210)***	(0.0860)	(0.0373)**	(0.0420)***	(0.0615)	(0.1052)***
Individual-Level Variables						
Violent Crime Type	0.2108					
	(0.0184)***					
Property Crime	-0.6712					
	(0.0125)***					
Drug Crime	0.1383					
	(0.0113)***					
Public Order Crime	-0.7711					
	(0.0137)***					
Immigration Crime	-0.3141					
	(0.0168)***					
Age	0.0007	-0.0094	0.0030	0.0036	-0.0048	0.0005
	(0.0003)***	(0.0015)***	(0.0004)***	(0.0006)***	(0.0007)***	(0.0009)
Female	-0.4429	-0.5129	-0.3459	-0.3814	-0.5508	-0.4401
	(0.0069)***	(0.0606)***	(0.0088)***	(0.0196)***	(0.0258)***	(0.0367)***
Black	0.1291	0.2245	-0.0498	0.4079	0.0093	-0.0487
	(0.0070)***	(0.0416)***	(0.0099)***	(0.0194)***	(0.0232)	(0.0388)
Hispanic	0.2360	-0.0302	0.0447	0.4498	0.1382	0.2193
	(0.0087)***	(0.0554)	(0.0138)***	(0.0198)***	(0.0264)***	(0.0363)***
Asian	-0.0393	0.0894	0.0104	0.1224	-0.3185	-0.0775
	(0.0162)**	(0.1127)	(0.0219)	(0.0434)***	(0.0425)***	(0.0536)
Less than High School	0.1776	0.2668	0.0260	0.2869	0.1013	0.2527
	(0.0077)***	(0.0453)***	(0.0116)**	(0.0166)***	(0.0234)***	(0.0353)***
High School Graduate	0.0368	0.1230	-0.0460	0.1511	-0.0044	0.1276
	(0.0071)***	(0.0384)***	(0.0101)***	(0.0137)***	(0.0198)	(0.0310)***
College Graduate	0.0623	-0.1396	0.0720	-0.1201	0.0171	-0.1099
	(0.0102)***	(0.0666)**	(0.0129)***	(0.0249)***	(0.0251)	(0.0453)**
Not an American Citizen	0.5529	0.5016	0.3721	0.6562	0.3606	0.5397
	(0.0113)***	(0.1149)***	(0.0190)***	(0.0347)***	(0.0424)***	(0.0473)***
Has Criminal History	0.4326	0.5149	0.4501	0.2756	0.4320	0.5433
	(0.0061)***	(0.0538)***	(0.0086)***	(0.0150)***	(0.0217)***	(0.0444)***
Number of Dependents	0.0006	0.0020	-0.0019	-0.0012	-0.0044	0.0056
	(0.0005)	(0.0023)	(0.0008)**	(0.0011)	(0.0016)***	(0.0010)***
State-Level Variables						
State Price Index	0.0143	0.0337	-0.0054	0.0663	-0.0191	-0.0722
	(0.0047)***	(0.0142)**	(0.0065)	(0.0088)***	(0.0114)*	(0.0179)***
Real Median H.H. Inc.	-0.0032	-0.0014	-0.0006	-0.0089	0.0004	0.0158
	(0.0005)***	(0.0019)	(0.0005)	(0.0008)***	(0.0012)	(0.0039)***
Dem. Prop. In Legis.	0.0246	0.5813	-0.1878	0.4579	0.2685	-0.7699
	(0.0735)	(0.4496)	(0.1327)	(0.1355)***	(0.2409)	(0.2735)***
In-State Federal Prisons	0.0877	0.2093	-0.0052	0.2745	-0.0567	-0.1594
	(0.0177)***	(0.0833)**	(0.0193)	(0.0333)***	(0.0439)	(0.0514)***
N	579,641	23,449	122,739	234,557	35,154	107,218

All estimates include state and yearly fixed effects.

Clustered standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure 1. **National papers related to privatization compared to national private prisons, by year**

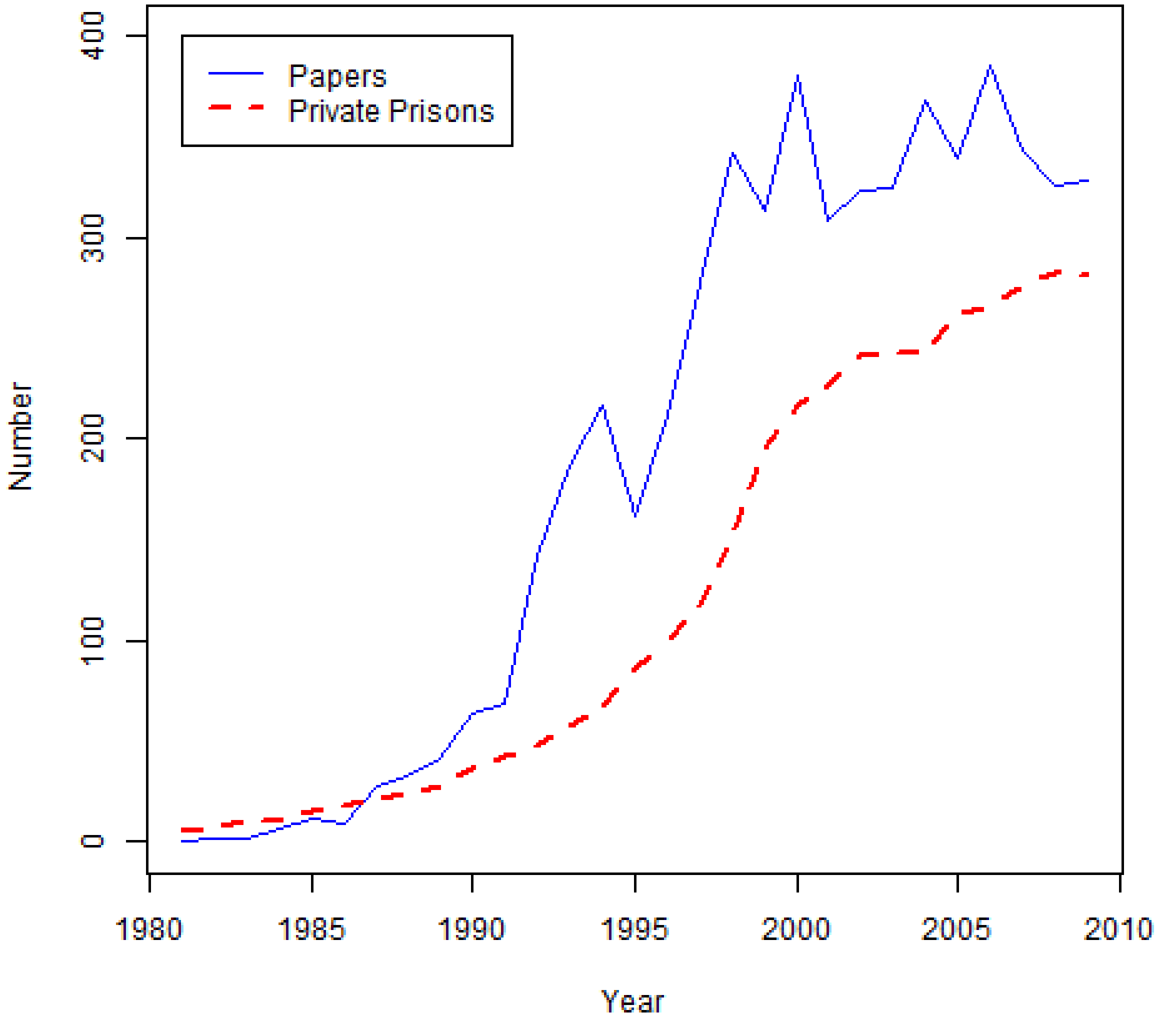

Figure 2. **Marginal extensive effect of a private prison by corruption level**