February 2011

Incarceration and Incapacitation: Evidence from the 2006 Italian Collective Pardon

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We thank Enrico Moretti for introducing the co-authors. We gratefully acknowledge financial support for this project from the National Science Foundation.

Abstract

This paper presents estimates of pure incapacitation effects based on variation in incarceration caused by an unusual policy event in the Italian corrections system. In August 2006, the Italian government released roughly one-third of the nation's prison inmates following the passage of national legislation aimed at relieving prison overcrowding. We estimate the reverse incapacitation effects using three sources of variation induced by this pardon. First, using national level monthly crime data, we test for a discontinuous break in national crime rates corresponding to the August 2006 mass release. Second, a simple mechanical model of incapacitation suggests that a massive one-time increase in the prison release rate should induce a dynamic adjustment process back towards steady-state values for both the crime rate as well as the incarceration rate. We use the variation along this adjustment path (ignoring the discontinuity) to provide a second estimate of the incapacitation effect. Finally, we exploit regional variation in prison releases based on the province of residence of pardoned inmates to estimate an alternative incapacitation effect using cross-province variation in the intensity of treatment. All three sources of variation yield estimates that are largely consistent with one another, with estimates of annual incapacitation effects on crimes reported to the police ranging from 13 to 28 crimes prevented per prison-year served. Nearly all of this impact is attributable to theft and robbery, with mixed evidence regarding other offense categories. We also conduct more general tests for an impact of the collective pardon on national level crime rates that do not pre-specify the timing of the structural break. The results from this analysis confirm the main findings regarding timing and the crimes impacted by the release.

1. Introduction

A growing body of econometric studies finds significant and in some instances quantitatively substantial causal impacts of incarceration on crime (Marvell and Moody 1994, Levitt 1996, Liedka, Piehl, and Useem 2006, Johnson and Raphael 2010). While estimate magnitudes are somewhat sensitive to estimation methodology, time period analyzed, and the overall incarceration level in the areas under study, most careful research finds that exogenous increases in incarceration rates generally lead to decreases in crime. However, the exact mechanisms driving this inverse relationship have proved difficult to pin down. Whether the crime-prison elasticity is driven primarily by deterrence or incapacitation is an open and actively researched empirical question.

The relative contribution of deterrence and incapacitation to the prison-crime relationship is more than a mere academic debate. A finer understanding of these causal channels would provide critical information important for both crime control policy as well as general theoretical research on criminal participation. With regards to policy, to the extent that potential criminals are deterred by severe punishment, optimal sentencing structures should emphasize stiff penalties over apprehension since the latter policy tool is resource-intensive while the former may in some instances decrease crime at zero cost (Becker 1968; Polinsky and Shavell 1984). On the other hand, if prison reduces crime primarily by incapacitating the criminally active, greater resources should be devoted to apprehension. Moreover, given the strong relationship between age criminal desistance, sentencing regimes that emphasize stiff (i.e., long) sentences when deterrence is relatively unimportant may in steady-state be incarcerating large numbers of inmates who have aged out of criminal activity.

More generally, being able to distinguish the relative importance of deterrence and incapacitation in explaining the prison-crime effect would inform theoretical reasoning regarding the decision to participate in criminal activity. The economic model of crime postulates the existence of a rational offender who weighs the expected costs and benefits and makes decisions accordingly, taking into account the relative rewards to crime and one's degree of risk aversion (Becker 1968). Alternative criminological and sociological theories emphasize human capital endowment, socialization towards anti-social norms, peer-influence, biology, and other criminogenic determinants of crime that do not fit neatly within the rational choice framework. A quantitative assessment of the relative importance of incentives as opposed to pre-determined characteristics for individuals whose criminal activity is either deterred or constrained by prison would provide information regarding which set of theories best describes the criminal behavior of the most serious offenders in society.

This paper presents what we argue to be lower-bound estimates of pure incapacitation effects based on variation in incarceration caused by an unusual policy event in the Italian corrections system. In August 2006, the Italian government released more than one-third of the nation's prison inmates following the passage of national legislation aimed at relieving prison overcrowding.[1] The collective pardon did not impact sentencing for future offenders who were not incarcerated at the time of the pardon and enhanced sentences for those pardoned offenders who reoffend within the five years following their early release. On net, these two factors likely induced a modest deterrent effect on criminal activity.[2] Hence, any observed increase in crime

[1] Data on prison population show a significant and longlasting problem of prison overcrowding. The ratio between prison population and prison capacity at 31st December was: 120% in 2000, 124.7% in 2001, 125.6% in 2002, 122.4 in 2003, 126.5% in 2004, 134.3% in 2005 and 138.2% in June 2006 before the 2006 August collective pardon (source: DAP – Ministero della Giustizia)

[2] For pardoned inmates, Drago, Galbiati, and Vertova (2009) demonstrate a substantial deterrent effect of the effective sentence enhancement. We discuss this research in greater detail below.

associated with the mass pardon arguably reflects a lower-bound incapacitation effect estimate – i.e., an estimate biased downward by deterrence. This is an unusual feature of this particular natural experiment as in most empirical studies of the crime-prison relationship, variation in incarceration rates induce deterrence and incapacitation effects that have similarly signed impacts on crime.

Our incapacitation effect estimates use three sources of variation. First, using national level monthly crime data, we test for a discontinuous break in national crime rate time series associated with the August 2006 mass release. The ratio of the crime rate discontinuity to the incarceration rate discontinuity provides our first estimate of the incapacitation effect. Second, a simple mechanical model of incapacitation suggests that a massive one-time increase in the prison release rate should induce a dynamic adjustment process back towards steady-state values for both the crime rate as well as the incarceration rate (Johnson and Raphael 2010). We use the variation along this adjustment path (ignoring the discontinuity) to provide a second estimate of the incapacitation effect. Finally, we exploit provincial variation in prison releases based on the province of residence of pardoned inmates to estimate an alternative incapacitation effect using cross-province variation in the intensity of treatment.[3] This latter strategy parallels the research by Barbarino and Mastrobuoni (2009) who study the crime effects of Italian pardons and amnesties occurring prior to the 2006 pardon. All three sources of variation yield estimates that are largely consistent with one another, with estimates of annual incapacitation effects on crimes reported to the police ranging from 13 to 28 crimes prevented per prison-year served. Nearly all of this impact is attributable to theft and robbery, with mixed evidence regarding other offense categories.

[3] The 103 Italian provinces (i.e. administrative Italian counties) correspond to the NUTS 3 Eurostat classification areas and are comparable in size to US counties. While the 20 Italian regions correspond to the NUTS 2 Eurostat classification.

We also conduct more general tests for an impact of the collective pardon on national level time series. In particular, we estimates a series of models that tests for structural breaks in the national level crime series without pre-supposing the timing of the break. To draw inference we rely both on asymptotic critical values for such tests derived in Andrews (2003) as well as critical values generated through Monte Carlo simulations as in Piehl et. al. (2003). The results from this analysis confirm our findings of structural breaks in total crime, theft, and robbery that correspond in timing to the August 2006 prisoner release.

2. The Causal Pathway Linking Incarceration and Crime Rates

Incarceration may impact the overall level of crime through several channels. First, incarceration mechanically incapacitates the criminally active. Second, the risk of incarceration increases the expected costs of crime and may thus deter potential offenders (an effect referred to as general deterrence). Finally, the incarceration experience may alter future offending relative to the counterfactual age-offending profile the individual would have experienced had he not been incarcerated. This effect could go in either direction. Prior prison experience may either reduce criminal activity among former inmates who do not wish to return to prison (referred to as specific deterrence) or enhance criminality if prior incarceration increases the relative returns to crime.

A large body of research by criminologists has focused on measuring pure incapacitation effects with nearly all of this research focused on the United States. Many such studies are based on inmate interviews regarding their criminal activity prior to their most recent arrest and then imputing the amount of crime that inmates would have committed from their retrospective responses (sometimes referred to by criminologists as the inmate's λ value). Results from this

research vary considerably across studies (often by a factor of ten), a fact often attributable to a few respondents who report incredibly large amounts of criminal activity (Ludwig and Miles 2007). The most careful reviews of this research suggest that on average each additional prison year served results in 10 to 20 fewer serious felony offenses (Marvell and Moody 1994, Spelman 1994, 2000). However, the usefulness of such studies for predicting the actual impact of incarcerating one more person on crime has been questioned based largely on the sensitivity of these estimates to outlier inmates as well as the possibility that those incapacitated may be subsequently replaced on the street by new offenders responding to the incarceration-induced vacancies (Ludwig and Miles 2007).

Most of this incapacitation research was conducted using prisoner surveys fielded during time periods when the U.S. incarceration rate was much lower than it is currently. As the incarceration rate increases one might expect the λ value of the marginally-incarcerated inmate to decline –i.e., the increased use of incarceration, as reflected in higher incarceration rates, may be netting consecutively less dangerous offenders. The findings from the more recent incapacitation study by Owens (2009) suggest that this is the case. Owens analyzes the criminal activity of convicted felons who serve less time as the result of a change in Maryland sentencing practices away from considering juvenile records when sentencing adult offenders. The author finds that these former prison inmates indeed committed additional crimes during the time period when they would have otherwise been incarcerated. However, the implied incapacitation effects are quite small, on the order of one-fifth the size of the incapacitation effects from earlier research.

By construction, the incapacitation studies provide only a partial estimate of the effect of incarceration on crime since they are unable to detect contemporary general deterrence. Several scholars have attempted to estimate the overall effect of incarceration using aggregate crime and

prison data. However, these studies must address an alternative methodological challenge; the fact that unobserved determinants of crime are likely to create a simultaneous relationship between incarceration and crime rates.

Marvell and Moody (1994) are perhaps the first to estimate the overall incarceration effect using state-level panel regressions. The authors use a series of granger causality tests and conclude that after first differencing the data, within state variation in incarceration is exogenous. They then estimate the effect of incarceration on crime using a first-difference model with an error correction component to account for the co-integration of the crime and prison time series. The authors estimate an overall crime-prison elasticity of -0.16.

Levitt (1996) also estimates the effect of incarceration on crime using a state level panel data model. Unlike Marvell and Moody, however, Levitt explicitly corrects for the potential endogeneity of variation in incarceration rates. Levitt exploits the fact that in years when states are under a court order to relieve prisoner overcrowding, state prison populations grow at a significantly slower rate relative to years when states that are not under such court orders. Using a series of variables measuring the status of prisoner overcrowding lawsuits as instruments for state level incarceration rates, Levitt finds 2SLS estimates of crime-prison elasticities that are considerably larger than comparable estimates from OLS with a corrected property crime-prison elasticity of-0.3 and a violent crime-prison elasticity of -0.4.

In more a recent analysis of state-level panel data, Johnson and Raphael (2010) use an instrument for incarceration based on the difference between a state's current incarceration rate and the state's steady-state incarceration rate implied by the observable contemporary prison admissions and release rates. The authors derive a theory-based empirical prediction regarding the impact of this difference in actual and steady-state crime rates on next-year's change in

incarceration and use this to instrument the actual incarceration rate. The authors find statistically-significant impacts of incarceration on crime. However, the joint incapacitation/deterrence effect of incarceration decline considerably in the U.S. as the incarceration rate increases. In a comparable analysis using time-series corrections similar to that of Marvell and Moody (1994), Liedka, Piehl, and Useem (2006) also find that the marginal impact of incarceration on crime has declined in the U.S. as the scale of incarceration has increased.

A recent study of Italian crime rates by Barbarino and Mastrobuoni (2009) is perhaps most relevant to our current analysis. The authors construct a panel data set of crime and incarceration rates that vary by year and by Italian region. To break the simultaneity between crime and incarceration the authors use the recurrent national-level collective pardons occurring between 1962 and 1995 as an instrument for regional incarceration rates. The authors find sizable impacts of prison on crime. In an accompanying cost-benefit analysis, the large incapacitation effect estimates coupled with estimates of the social costs of crime imply that mass pardons in Italy over the period studied are particularly socially expensive ways of relieving prisoner overcrowding.

There are a number of studies that have attempted to separately estimate the deterrent effect of incapacitation. Kessler and Levitt (1999) estimate the effect of sentence enhancements for violent crime on overall offending arguing that the crimes receiving the enhancement would have resulted in incarceration regardless and thus any short term effect of the enhancement on crime is attributable to pure deterrence. Webster, Doob, and Zimring (2006), however, argue that the deterrence estimates in Kessler and Levitt are driven by crime rates that were already trending downwards and thus are spurious. A separate set of studies attempts to estimate general

deterrence effects by exploiting the discontinuous increase in sentences for offenses occurred at 18 years of age. Levitt (1998) finds a decrease in offending when youth reach the age of majority while Lee and McCrary (2009) find no evidence of such an effect.

Most recently, Drago, Galbiati and Vertova (2009) present evidence regarding deterrent effects induced by the 2006 Italian collective pardon that we study here. The Italian pardon released most inmates with three years or less remaining on their sentence. Those who re-offend face an enhanced sentence through the addition of their un-served time to whatever new sentence is meted out. The authors exploit the fact that among pardoned inmates with similar offenses and sentences, those who are admitted to prison closer to the date of the pardon faced a larger post-release sentence enhancement than those who are admitted to prison at earlier dates. The authors demonstrate statistically significant and substantially higher recidivism rates among those pardoned inmates facing lower effective sentence enhancement.

In what follows, we present estimates of the incapacitation effect caused by this pardon. Comparison of our findings to the existing body of research estimating joint incapacitation/deterrence effects will permit characterization of the relative importance of incapacitation in explaining the crime-preventing impacts of incarceration.

3. Description of the 2006 Italian Pardon and our Estimation Strategy

On July 31, 2006 the Italian Parliament passed the Collective Clemency bill that greatly reduced the sentences of inmates convicted of certain felony offenses prior to May 2, 2006. The pardon reduced the residual sentence (i.e., the time remaining to be served) of eligible inmates by three years effective August 1, 2006. As a result, most inmates with less than three years to serve as of this date were immediately released. Subsequent releases occurred (and will occur) as

remaining sentences fall to 36 months, though roughly 80 percent of all those who will eventually be released under the pardon were released on August 1, 2006.[4] Inmates convicted of offenses involving organized crime, felony sex offenders, and those convicted of terrorism, kidnapping, or exploitation of prostitution are ineligible for early release (Drago, Galbiati, and Vertova 2009). Pardoned inmates are not subject to any form of post-release supervision. However, those who are re-arrested and convicted for a crime receiving at least a two-year sentence during the five year period following release have the full residual sentence from their pardoned offense added to the sentence imposed for the subsequent crime.

According to the historical narrative presented in Drago, Galbiati, and Vertova (2009), the passage of the Collective Clemency bill followed a six year debate surrounding Italian prison conditions, spurred in large part by the activism of the Catholic Church and the personal involvement of Pope John Paul II. With Italian prisons filled to 130 percent of capacity, the pardon was principally motivated by the need to address overcrowding. While the 2006 Clemency bill was the only such collective pardon in recent times, Italy has a long history of such pardons and in some instances, amnesties dating back to the 19th century. According to Barbarino and Mastrobuoni (2009), collective pardons occurred with relative frequency during the post-WW II period. However, since the 1992 change to the Italian constitution requiring a two-thirds majority vote in the parliament, there were no pardons until the 2006 event (with the most recent prior pardon occurring in 1990).

Figure 1 displays a scatter plot of Italian monthly incarceration rates (measured as inmates per 100,000 residents) for the period spanning January 2004 through January 2009. Months are measured relative to August 2006, with August 2006 taking the value of zero. The figure also plots quadratic regression functions for the period between January 2004 and August

[4] In particular, more than 90% of pardoned inmates had been released by the end of August 2006.

2006 and the period from September 2006 through December 2008. In addition to the period-specific regression functions, the figure also presents 95 percent confidence intervals for the predicted values of the regression functions (shaded in gray). The figure depicts a relatively stable incarceration rate that increases slightly between January 2004 and August 2006. Between August and September 2006, the collective pardon induces a sharp decline in the national prison population. Over this one-month period, the prison population declines by 21,863 individuals, equivalent to a 36 percent decrease, with a corresponding decrease in the national incarceration rate from 103 to 66 inmates per 100,000. Between September 2006 and December 2008 the incarceration rate steadily increases to the point where by December 2008 the incarceration rate of 98 is only slightly less than the pre-pardon high in August 2006 (103).

In this section, we first describe the channels through which the collective pardon may have influenced national crime rates and argue that the effects if any serve as lower-bound estimates of incapacitation. We also use this discussion to spell out our empirical identification strategy. Finally, we discuss our data.

Channels linking the pardon to crime and our principal methodological strategy

The collective pardon depicted in Figure 1 may have impacted national crime rates through several channels. First, consider those potential criminal offenders who are not incarcerated at the time of the pardon. For this population, the pardon does not alter the expected sentence associated with being caught, prosecuted, and convicted of a crime, since the clemency bill did not alter Italian sentencing policy. One might argue that the pardon may impact one's expectations regarding the likelihood of a future pardon. By extension, this would alter subjective assessments of the expected value of time served should one be caught and convicted. Barbarino and Mastrobuoni (2009) argue that the impact on expectations can go in either

direction. The demonstrated ability to muster the two-thirds majority needed to pass the clemency bill may indicate to some that such actions in the future are possible. Alternatively, the size and scope of the 2006 pardon substantially relieved pressure to address overcrowding, bringing the nation's prison population below system capacity, reducing pressure for and the likelihood of subsequent pardons in the foreseeable future.

While one cannot assess the effect on expectations with any degree of certainty, we believe that the pardon likely had little effect on expectations regarding future pardons. Prior to the 2006 Clemency bill several attempts to push such bills through the parliament failed (Drago et. al. 2009) and hence expectations regarding an early release prior to the 2006 legislation were likely to already be quite low. If anything, the diminished pressure to relieve prison overcrowding should lead potential offenders to lower their expectations regarding the likelihood of future pardons. To the extent this is true, the pardon would induce a negative deterrent effect on crime committed by those not incarcerated in August 2006, imparting a negative bias to our incapacitation effect estimates.

Next, consider the criminal behavior of those who are released as a result of the pardon. By virtue of their conviction and incarceration, past behavior has revealed a relatively high propensity to commit crime. Releasing these inmates into non-institutional society should mechanically lead to an increase in crime rates via a reverse incapacitation effect. On the other hand, the looming sentence enhancement should a pardoned inmate reoffend would reduce criminal activity below what it otherwise would have been via general deterrence (precisely the finding in Drago, Galbiati, and Vertova 2009).

To illustrate the likely impacts of the pardon on crime operating through incapacitation as well as our identification strategy, here we present a simple mechanical model of incapacitation

similar to that presented in Johnson and Raphael (2010). We interweave into the discussion the empirical equations that we estimate to measure incapacitation. As we will soon see, the model provides quite strong predictions regarding the immediate crime effects of the pardon as well as the long-term dynamic adjustment of both prison population as well as crime.

Suppose that all members of the national population can be defined as either incarcerated or not incarcerated. The distribution across these two states at a given time t is given by the share vector, $S_t'=[S_{1,t}\ S_{2,t}]$, where $S_{1,t}$ is the proportion not incarcerated at time t, $S_{2,t}$ is the proportion incarcerated at time t, and $S_{1,t}+S_{2,t}=1$. Suppose that the likelihood that any non-institutionalized member of society commits a crime is given by c, that the likelihood of being caught and convicted conditional on committing a crime is given by p, and that the likelihood of being released from prison in any given period is given by the parameter θ. Higher values of this parameter are associated with shorter prison sentences. The parameter c represents the incapacitation effect that we wish to uncover (the crimes per capita prevented per period by incarcerating one additional person). In what follows we analyze how a one-time temporary shock to θ can be used to uncover this criminality parameter.

With the definition of these three parameters, we can define the transition probability matrix between states of the world as

(1)
$$T=\begin{bmatrix}1-cp & cp \\ \theta & 1-\theta\end{bmatrix}$$

where 1-cp is the transition probability from not-incarcerated to not-incarcerated, cp is the incarceration hazard for the non-incarcerated, θ is the release hazard for the incarcerated and 1-θ is the transition probability from incarcerated to incarcerated. With the transition matrix, the population share vector evolves over time according to the equation

$$S'_t = S'_{t-1}T. \tag{2}$$

The specific equations describing each sub-population are derived by expanding equation (2):

$$\begin{aligned} S_{1,t} &= S_{1,t-1}(1-cp) + S_{2,t-1}\theta \\ S_{2,t} &= S_{1,t-1}cp + S_{2,t-1}(1-\theta) \end{aligned} \tag{3}$$

Finally, assuming that the institutionalized do not commit crime, the nation's crime rate in year t will equal the proportion of the population not incarcerated multiplied by the criminality parameter, or

$$Crime_t = cS_{1,t}. \tag{4}$$

To analyze the short and long term effects of a collective pardon on crime and incarceration rates, we begin by assuming that the system is in steady state. We then shock the system with a one-time temporary increase in the prison release rate. Steady state is defined by the condition $S'_t = S'_{t-1} = S'$. With the transition matrix T, the steady-state population shares are given by

$$\begin{aligned} S_1 &= \frac{\theta}{cp+\theta} \\ S_2 &= \frac{cp}{cp+\theta}. \end{aligned} \tag{5}$$

Between any two periods, the change in the incarceration rate equals the proportion of the population admitted to prison during the period minus the proportion of the population that is released. In steady state, the overall change and the two component parts of the change are given by

$$\Delta S_2 = \frac{cp\theta}{cp+\theta} - \frac{\theta cp}{cp+\theta} = 0 \tag{6}$$

where the first term provides the proportion of the national population flowing into prison, the second term is the proportion flowing out, and where the two components sum to zero by definition. A stable proportion incarcerated implies a stable proportion not incarcerated. This in turn, implies a stable (i.e., unchanging) crime rate by virtue of equation (4).

The collective pardon is roughly equivalent to a one-time temporary increase in the release probability. Suppose that the system in steady state is shocked by a change in the release parameter from θ to θ', where θ'> θ. The change in the incarceration rate between the two periods surrounding the collective pardon is equal to

(7) $$\Delta S_2 = \frac{cp\,\theta}{cp+\theta} - \frac{\theta' cp}{cp+\theta} = \frac{cp\,[\theta-\theta']}{cp+\theta} < 0.$$

Here, releases (the second term) exceed admissions (the first) and thus the incarceration rate decreases. The crime equation (4) implies that the change in the crime rate will be equal to the criminality parameter times the change in the proportion not incarcerated. Since the two population shares must sum to one, we know that $\Delta S_1 = -\Delta S_2$. Hence, the change in crime rates between the two periods surrounding the pardon is given by

(8) $$\Delta Crime = -c\Delta S_2 > 0.$$

Notably, the ratio of the change in (8) to the change in (7) identifies the criminality parameter *c*.

Our first empirical strategy for measuring the incapacitation effect uses high frequency crime and incarceration data to estimate the changes in equations (7) and (8). Specifically, using monthly data we first define a monthly time variable, *t*, measuring month relative to August 2006 (with August 2006 taking on the value of zero). We then estimate the univariate time-series equations

$$Crime_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \beta_0 Break_t + \beta_1 Break_t * t + \beta_2 Break_t * t^2 + \varepsilon_t$$
$$Incarceration_t = \delta_0 + \delta_1 t + \delta_2 t^2 + \phi_0 Break_t + \phi_1 Break_t * t + \phi_2 Break_t * t^2 + \eta_t$$

(9)

where the indicator variable Break_t is set equals to one for t>0 and set equal to zero otherwise, the terms $\alpha_o, \alpha_1, \alpha_2, \beta_0, \beta_1, \beta_2, \delta_0, \delta_1, \delta_2, \phi_0, \phi_1$, and ϕ_2 are parameters to be estimated, and ε_t and η_t are disturbance terms. The change in crime for the two months surrounding the collective pardon can be constructed by summing the coefficient estimates for $\alpha_1, \alpha_2, \beta_o, \beta_1$ and β_2 with the coefficient on the break dummy variable, β_0 roughly interpretable as the counterfactual treatment effect of the collective pardon at t=0 (Angrist and Pischke 2009). We use the empirical estimate of β_0 to approximate the change in crime in equation (8).[5] The corresponding approximation of equation (7) is given by the coefficient on the break variable in the incarceration equation, ϕ_0. Negative one times the ratio of these two parameters (i.e., $-\beta_0/\phi_0$) provides a structural estimate of the incapacitation effect as measured by the parameter c in the model above. Below we estimate the equations in (9) for crime overall, for crime rates pertaining to specific offenses and for the incarceration rate and use the break coefficients to estimate the reverse incapacitation effect induced by the pardon.

The incapacitation parameter can also be identified using the variation along the dynamic adjustment path for incarceration and crime that is induced by the one-time shock. To illustrate this alternative strategy, note that the incarceration process described in equation (3) in conjunction with the adding-up constraint $S_{1,t} + S_{2,t} = 1$ yields the following first-order difference equation relating incarceration in time t to incarceration in time t-1:

(10) $$S_{2,t} + (cp + \theta - 1)S_{2,t-1} = cp.$$

[5] We also estimated these incapacitation effects using the sum of coefficients giving the pre-post change. These estimates are qualitatively and quantitatively similar to those estimated based on the break term coefficients alone.

Solving this difference equation yields an expression for the incarceration rate at any given time equal to the sum of the eventual steady-state rate and an adjustment factor reflecting the movement towards the steady state. The solution for equation (10) is

$$S_{2,t} = A(1 - cp - \theta)^t + \frac{cp}{cp + \theta}, \tag{11}$$

where A is a constant that can be definitized if one specifies initial conditions at time t=0. To graft this process onto our example of the collective pardon, suppose that the collective pardon causes a one-period increase in the release parameter from θ to θ' and that the release parameter then returns to the lower value θ. Hence, ultimately the incarceration rate will return to the old steady-state value (the second term in equation (11)) after an adjustment period. To definitize equation (11) redefine the time variable such that t=0 at the first period following the pardon. From the change in incarceration rates described in equation (7) and the steady-state incarceration rate described in equation (5) we know that the incarceration rate in the period following the pardon is equal to

$$S_{2,0} = \frac{cp}{cp + \theta} + \frac{cp[\theta - \theta']}{cp + \theta} = \frac{cp[1 + \theta - \theta']}{cp + \theta}. \tag{12}$$

Evaluating equation (11) at t=0 and setting this equal to the expression in (12), we can then solve for A. Plugging this solution back into equation (11) gives an equation that described the post-pardon adjustment process for the national incarceration rate:

$$S_{2,t} = \frac{cp[\theta - \theta']}{cp + \theta}[1 - cp - \theta]^t + \frac{cp}{cp + \theta}. \tag{13}$$

The solution in equation (13) yields several implications. First, we note that the solution for the constant A in the first term on the right hand side of (13) is the one period change in

incarceration induced by the collective pardon. We have already demonstrated that this term is negative. This is multiplied by an adjustment factor given by $(1\text{-}cp\text{-}\theta)^t$. The term in parentheses is positive yet considerably less than one and hence as time passes the adjustment factor will approach zero. The second term in equation (13) is the steady state value for incarceration that will eventually be reached with sufficient time and stable parameters. Together, the sum of the negative and vanishing adjustment term and the steady state term imply that following the initial decrease in the incarceration rate, the incarceration rate will then steadily increase back to the original steady-state level. This is precisely what we observe empirically in the national incarceration rate time series depicted in Figure 1.

To derive the adjustment path for the crime rate, we first need to derive the adjustment path for the proportion non-institutionalized. Since the proportion not incarcerated is simply one minus the proportion incarcerated, from equation (13) we find

$$S_{1,t} = -\frac{cp[\theta - \theta']}{cp + \theta}[1 - cp - \theta]^t + \frac{\theta}{cp + \theta}. \tag{14}$$

Multiplying the expression in equation (14) by c gives the adjustment process for the crime rate as a function of time:

$$Crime_t = -c\,\frac{cp[\theta - \theta']}{cp + \theta}[1 - cp - \theta]^t + \frac{c\theta}{cp + \theta}. \tag{15}$$

Similar to our discussion of the incarceration rate equation, this adjustment process suggests that the crime rate should follow a distinct path in response to a one time temporary increase in release rate. Specifically, the first term in equation (15) is equal to $-c$ multiplied by the immediate decline in incarceration caused by the pardon $\left[\frac{cp[\theta - \theta']}{cp + \theta}\right]$, which is then multiplied by the positive adjustment coefficient that vanishes with time. Hence, the first term on the right

hand side of equation (15) is positive and diminishing as t increases (i.e., is the largest at t=0). The second term on the right hand side of (15) is the steady-state crime rate implied by the parameters of the process. Together these two terms imply that the time path of the crime rate should be the mirror image of the time path of the incarceration (a sharp increase followed by a more gradual reduction towards the pre-pardon steady-state).

To identify the incapacitation effect from the dynamic adjustment path, we must first difference the incarceration equation (13) and the crime equation (15) for any two time periods such that the base time period satisfies t>0. Defining $\Delta S_{2,t}$ and $\Delta Crime_t$ as the changes in incarceration rates and crime rates between periods t and t+1. Equations (13) and (15) give

(16)
$$\Delta S_{2,t} = -\frac{cp[\theta - \theta']}{cp+\theta}[1-cp-\theta]^t(cp+\theta)$$

and

(17)
$$\Delta Crime_t = c\frac{cp[\theta - \theta']}{cp+\theta}[1-cp-\theta]^t(cp+\theta)$$

respectively. Similar to identification using the structural breaks surrounding the pardon, taking the ratio of equation (17) to equation (16) identifies the incapacitation parameter c. Note, here we identify c only using variation in incarceration and crime reflecting the long-term adjustment response to the shock caused by the pardon, not including the variation induced by the initial shock. This identification strategy is identical to that pursued in Johnson and Raphael (2010).

To operationalize this strategy in terms of the regression parameters depicted in equation (9), one would simply first difference the crime equation and the incarceration equation for any two periods in the post-structural break time series. In terms of the parameters of these functions, we get empirical analogs for equations (16) and (17) equal to

(18) $$\Delta Incarceration_t = \delta_1 + \phi_1 + (\delta_2 + \phi_2)(2t+1)$$

and

(19) $$\Delta Crime_t = \alpha_1 + \beta_1 + (\alpha_2 + \beta_2)(2t+1).$$

With estimates of the two regression functions, both changes in equations (18) and (19) can be easily constructed from the parameter estimates. The ratio of the predicted crime change to the predicted incarceration change (multiplied by negative one) provides an alternative estimate of the incapacitation effect.

Limits to this mechanical incapacitation model and implications for the interpretation the of empirical results

Our simple model yields very strong empirical predictions that can be easily evaluated with high-frequency national data. However, there are several limitations to this model that should be noted as they impact how one should interpret the empirical results we present below.

First, the model is non-behavioral. To the extent that released inmates are partially deterred from committing crime (either along the extensive or intensive margins) by the sentence enhancement associated with their residual sentence, the incapacitation effect that we can measure with national data will be downward biased. Indeed, Drago, Galbiati and Vertova (2009) find a substantial and significant deterrent effect of this implicit sentence enhancement. The extent of the downward bias will depend on several factors including the average value of the residual sentence and the proportion of offending committed by pardoned inmates as opposed to offenders not incarcerated at the time of the clemency bill. This lends further support to our interpretation of the estimates below as lower-bound incapacitation effects.

Second, our model assumes a constant propensity to commit crime among all members of society, with the impact of incarceration on crime occurring principally through variation in the size of the population at risk of committing a crime (i.e., the non-incarcerated). In reality, the

parameter, c, most certainly varies across the population at large as well as among the population of the criminally active. Assuming that those with the highest value of c are the most likely to be apprehended and incarcerated, we must interpret our estimated incapacitation effects as local average treatment effects. In fact, one might expect the incapacitation effect to vary at different levels of incarceration, assuming that the most criminally active are apprehended and incarcerated first.

Additional tests for incapacitation

The strategy that we have outlined thus far relies on national level data to identify incapacitation. An alternative strategy would be to exploit geographic variation across Italy's 103 provinces and exploit heterogeneity in the effective treatment received by difference provinces. Since the pardon was instituted at the national level, geographic variation in the scale of prison releases should be independent of the underlying determinants of crime trends for each locality (i.e., none of the unobserved determinants of provincial crime levels are driving either the pardon or the distribution of prison releases across localities). Thus, the inflow of former inmates returning to any specific province represents an exogenous shock to the locality's crime fundamentals.

To be specific, define the variable $Crime_i^{pre}$ as the average monthly crime rate (defined per 100,000 residents) for province i (where $i \in [1,\ldots,103]$) for some defined pre-pardon period (for example, the four month period preceding the pardon). Define the comparable variable $Crime_i^{post}$ as the average monthly crime level for province i for a defined post-pardon period, and the variable Δ_i^{2006} by the equation

$$\Delta_i^{2006} = Crime_i^{post} - Crime_i^{pre}. \tag{20}$$

Finally, define the variable *releases$_i$* as the number of those pardoned inmates whose last known residence prior to incarceration was in province *i* (measured as releases per 100,000 local residents). Our second strategy involves estimating the equation

$$\Delta_i^{2006} = \alpha + \beta releases_i + \varepsilon_i$$

(21)

where α, β, and δ are parameters to be estimates, and ε_i is a mean-zero random disturbance term. The coefficient β provides our alternative estimate of the impact of one additional released inmate per 100,000 local residents on the change in the number of crimes per 100,000 local residents.

As a final robustness check on the national level data analysis, we also test for structural breaks in national crime series without pre-specifying the date of the structural break. To the extent that the mass pardon induced increases in crime rates, the data should reveals a significant structural break that coincides in timing with the mass pardoning of inmates. We present a more thorough discussion of this robustness check along with the presentation of the results.

Description of the data

We draw on three sources of data for this project. First, we use data on crimes reported to the police measured at the monthly level for each Italian province for the period from January 2004 through December 2008. This data comes from the Ministero dell'Interno. We also employ monthly national prison population data, compiled by MInistero della Giustizia, for the same time period. For the national level analysis, we aggregate the provincial data to the national level.

We have also been provided with microdata on all inmates pardoned by the 2006 Collective Clemency bill. Included in these microdata is information on the province of residence of each pardoned inmate. We use this information in conjunction with the assumption

that inmates return to their province of residence preceding their incarceration to tabulate the number of releases per 100,000 provincial residents.

In what follows, we test for effects on overall crime and on twelve mutually exclusive and exhaustive crime categories. Table 1 presents average monthly crime rates for the entire period and for each year in our analysis period. The majority of crimes occurring in Italy are non-violent property crimes (with theft accounting for nearly 60 percent of crime overall). The annual averages suggest higher crime in 2006 and the highest average monthly crime rates in 2007, a pattern consistent with an impact of the collective pardon. We now turn to a more detailed analysis of the monthly data.

4. Empirical Results

Before presenting formal estimates of incapacitation effects, we begin with a graphical inspection of the national-level crime rates. Figure 2 presents a scatter plot of the total monthly crime rate against month measured relative to August 2006. In addition to the data points, the figure displays fitted quadratic time trends for the pre and post-pardon periods as well as the 95 percent confidence intervals for each point on the fitted trend. The figure reveals monthly total crime rates that are increasing slightly during the pre-pardon period, a discrete increase in crime between August 2006 and September 2006 and then a steady decline in monthly crime rates back to pre-pardon levels.

Figures 3 through 13 present comparable figures for each of the individual crime rates listed in Table 1. Figures 3 and 4 depict the time series for non-sexual violent crime rates and for the sexual assault rate. There is little visible evidence of an impact of the pardon on violence. We observe no notable positive break in trend corresponding to the pardon and post-pardon crime

paths that follow an inverted U-shape. In contrast, the theft and robbery rates (Figures 5 and 6) exhibit very large pre-post pardon increases in crime and steady declines in crime below pre-pardon levels for theft and to pre-pardon levels for robbery. Recall from Table 1 that theft constitutes nearly 60 percent of all crime in Italy. Hence, the observed effects in Figures 5 and 6 account for much of the increase in total crime observed in Figure 2. Of the remaining crime categories, vandalism and drugs/contraband exhibit a visible break in trend corresponding to the timing of the pardon. However, the breaks are small, with the end-points of the two trends (August 2006 and September 2006) lying within the confidence intervals for the opposing time trends.

Table 2 presents estimates for various specifications of the regression function underlying the total crime trends in Figure 2 and the total incarceration trends in Figure 1. Note these regression functions correspond to the regression models that we outlined in equation (9) above and provide key parameters for our two estimates of the incapacitation effect. For the crime and incarceration dependent variables we estimate four model specifications. The first model includes a quadratic time trend, a dummy indicating post-August 2006, and interaction terms between the quadratic trend variables and the post-pardon dummy. The second specification adds month fixed effects to account for seasonality in crime rates. The third specification adds year fixed effects. The final model specifies the error term in each equation as following an AR1 process.[6]

Panel A presents results for total crime. The coefficient on the post-pardon dummy provides formal estimates of the reduced-form effect of the pardon on crime. This coefficient is significant at the one percent level of confidence in all model specifications. In the base

[6] There is little evidence of serial correlation in any of the crime equation error terms. The incarceration rate, however, does exhibit serial correlation.

specification (model 1) there is a pre-post pardon increase in total crimes of approximately 51 per 100,000. Adding month effects increases the estimate to roughly 59, while adding year effects and correcting for serial correlation leads to slightly lower estimates of the break (58 and 57 additional crimes per 100,000 respectively). Regarding the time trends coefficients, the pre-pardon linear time trends are statistically insignificant as are three of the four coefficients on the pre-pardon quadratic trend terms. During the post-pardon period, however, crime rates significantly trend downward in all but the base specification.

Turning to the incarceration rate models in panel B, the estimates of the pre-post pardon declines in incarceration are large and statistically significant at the one percent level of confidence in all model specifications. In the three models assuming an iid error term, the decline in the incarceration rate is roughly 43 inmates per 100,000. Adjusting for serial correlation yields a slightly smaller decrease of 38 inmates per 100,000. In all four models, incarceration rates trend upward at a differentially faster pace following the August 2006 pardon.

As was discussed above, the coefficient estimates from the models presented in Table 2 can be used to estimate incarceration incapacitation effects. Specifically, taking the ratio of coefficient on post-pardon from the crime equation to the comparable coefficient from the incarceration equation and multiplying by negative one yields an estimate of the amount of crime prevented per prison-month served based on the instant variation in these series caused by the pardon.[7] Additionally, the coefficient estimates can be used to tabulate the changes in crime and incarceration along the post-pardon adjustment path as measured by the predicted time trend during the post-August 2006 period (corresponding to equations 18 and 19 above). The ratio of the implied one period change in crime to the corresponding one period change in incarceration

[7] Note, this estimate is equivalent to estimating the effect a just-identified IV model of crime on incarceration where post-pardon is used as an instrument for incarceration and the remaining set of exogenous variables includes a time trend, its square, and interaction terms between these two trend variables and the post-pardon indicator.

multiplied by negative one provides an estimate of the incapacitation effect of a prison month using only variation associated with the dynamic reaction to the pardon.

Table 3 presents incapacitation effect estimates using these two sources of variation based on each model specification in Table 2. For the sake of comparison to previous empirical research, we have annualized the incapacitation effect estimates and have adjusted the standard errors accordingly. The first column of figures gives annual incapacitation effect estimates based on the structural breaks in trend. The second through fifth column present incapacitation effect estimates based on variation along the adjustment path measured at six, twelve, eighteen and 24 months following the pardon. The incapacitation effects identified by the structural breaks in crime and incarceration suggest that each prison year served prevents 14 to 18 crimes, with the estimate from model (4) being the largest. All estimates are statistically significant at the one percent level of confidence.

The annual incapacitation effects based on the dynamic adjustment of crime and incarceration are generally larger than the estimates based on the discrete breaks in the time series, though the two sets of estimates lie within each other's confidence intervals. With the exception of the estimates from the base model, the incapacitation effects along the dynamic adjustment path do not appear to depend on the specific month anchoring the measurement. For models (2) through (4), the estimates suggest that each prison year served prevents between 24 and 37 crimes per year. The results for the base specification in model (1) suggest much larger incapacitation effects 24 months following the pardon (47 crimes) relative to six months following the pardon (22 crimes). However, the standard errors are fairly large for this specification. All of the incapacitation effect estimates using the dynamic adjustment path are significant at the one percent level of confidence with the exception of the estimate at t=6 for

model (1) (significant at the 10 percent level) and the estimate for t=24 for model (4) (significant at the five percent level of confidence).

Table 4 presents a limited set of regression results for specific offenses. For each offense the table presents the coefficient on the post-pardon dummy variable for each of the four model specifications used in Table 2. Here we suppress the remaining coefficients to conserve space. However, we will soon use these additional parameter estimates to measure implied incapacitation effects along the dynamic adjustment path of each crime. The estimates in Table 4 generally parallel what we gleaned from the graphical analyses. Specifically, there are relatively large and statistically significant (at the one percent level) increases in crime corresponding to the month of the pardon for thefts and robbery. The increase in theft accounts for 70 to 90 percent of the overall increase in crime, while the increase in robbery accounts for a relatively smaller share.

There are several notable differences relative to the graphical results. In particular, adjusting for month effects turns the coefficients positive for non-sexual violent crime and marginally significant in specifications (2) and (3). A similar pattern is observed for other crime, where models (2) and (3) yield increases in crime that are statistically significant at the one percent level of confidence. There is also some evidence of a slight increase in vandalism and drugs/contraband offenses.

Table 5 presents corresponding incapacitation effect estimates for specific offenses. Here we present estimates based both on the break in crime trend as well as the coefficients measuring the dynamic response of crime to the pardon. To conserve space, we only present estimates from the model inclusive of month and year effects and that corrects for serial correlation. Regarding the result identified with the shift in the crime intercept, we find an annualized incapacitation

effect of 13 crimes per 100,000 or theft/receiving stolen property and 0.63 crimes per 100,000 for robbery. All other estimates are insignificant, although we observe a slight and statistically significant decrease in incidents involving solicitation of a prostitute.

The annualized incapacitation effect estimates identified with the dynamic adjustment path, when significant, are generally larger than the estimates from the time series discontinuities. For theft, the estimated effect is largest six months following the pardon (44 incidents per 100,000) and then decreases as time passes (to 22 incidents 24 months following the pardon). A similar pattern is observed for robbery. There are several crimes that register significant incapacitation effects along the dynamics adjustment path but no effect when identified by the measured discrete change in crime. In particular, we find significant effects for sexual assault at twelve and eighteen months following the pardon, significant effects for drugs/contraband offenses at twelve and eighteen months and significant effects for soliciting a prostitute at eighteen and twenty-four months.

How do these results compare to prior incapacitation effect estimates? As we discussed in the literature review, the criminological literature attempting to measure pure incapacitation through inmate surveys generally gives pure incapacitation effect estimates ranging between 10 and 20 offenses per prison year. Our estimates are on the high end of this range, but generally consistent with this research. As much of this survey research was conducted in the United States at a time when the incarceration rate was considerably lower than it is today and much closer to that of Italy, the findings from this body of research present a particularly appropriate benchmark.

Regarding evidence from panel data studies, Johnson and Raphael (2010) estimate that for the period between 1978 and 1990 each additional prison year served in the U.S. prevented

on average fourteen reported serious crimes (11.4 property crimes and 2.5 violent crimes). This corresponded to a period when the average state incarceration rate was 186 per 100,000, roughly double the Italian incarceration rate over the period we are studying. Since the estimates in Johnson and Raphael represent the joint effect of incapacitation effect and general deterrence, our estimates based on the study of collective clemency suggest that the average incapacitation effect in Italy at this point in time are considerably larger than the measurable incapacitation effect in the United States during the 1980s.[8]

An alternative manner of characterizing the results here for the purposes of comparison to previous research would be to express the impacts as crime-prison elasticities. Using crime and incarceration rates in August 2006 as base values, the discrete increase in crime and decrease in incarceration from our most complete model specification yields a total crime-prison elasticity of -0.4. Measuring crime and incarceration changes along the dynamic adjustment path at six, twelve, eighteen, and twenty-four months following the pardon yields total crime-prison elasticities of -0.66, -0.59, -0.55, and -0.53 respectively. For the earlier period studied in Johnson and Raphael (2010) they find crime-prison elasticities of -0.43 for property crime and -0.79 for violent crime (with the overall average closer to property crime given its much greater relative frequency). Levitt's 1996 study using prison-overcrowding litigation as an instrument reports crime-prison elasticities of between -0.38 and -0.42 for violent crime and -0.26 and -0.32 for property crime. Perhaps the most relevant comparison is the study by Barbarino and Mastrobuoni

[8] Johnson and Raphael (2010) find considerably smaller joint incapacitation/deterrence effects in the U.S. for the period 1991 through 2004 when the average state incarceration rate was 396 inmates per 100,000. In particular, they find total reported crimes prevented per prison year during this latter period of approximately 3, with 2.6 of the incidents property crime. The relatively large incapacitation effects for Italy relative to the estimates for the U.S. during the 1980s, in conjunction with the even smaller effects for the latter period in the U.S. suggest that the crime prevention effects of incarceration do indeed decline as the incarceration rate increases to the relatively high levels experienced in the United States in recent years.

(2009) analyzing the impact of earlier collective pardons in Italy using region level annual data. The authors report total crime-prison elasticities of between -0.25 and -0.30.

5. Incapacitation-Effects Based on Cross-Regional Analysis and Testing for Structural Breaks in the Time-Series Without Pre-Specifying the Date

Thus far our estimates of the reverse incapacitation effect induced by the 2006 Collective Clemency Act have relied entirely on national level time series variation in crime and incarceration. The data reveal sharp breaks in overall crime with most of this attributable to increase in property crime associated with mass pardon, and post-pardon adjustment paths in crime and incarceration rates largely consistent with a simple mechanical model of incapacitation. In addition to this national level variation, the pardon induced considerable sub-national variation in the number of returned inmates per 100,000. On average, each of Italy's 103 provinces received approximately 33 pardoned inmates per 100,000 residents.[9] However, there was considerable variance in this variable across provinces with a cross-province standard deviation of 17, and values at the 10th, 25th, 75th, and 90th percentile of 16.46, 20.24, 44.04, and 52.67, respectively.

The impact of a returned prisoner on local crime rates is likely to depend on a host of factors, including the economic circumstances of the province, the number of police on hand to monitor and respond to the influx of released inmates, and perhaps the level of crime (an indicator of the current police workload) in the province immediately prior to the pardon. Such potential heterogeneity poses interesting research and policy questions in its own right and should be explored in the future. Here, we simply assess whether provinces receiving more released inmate per resident experience larger increases in crime. This cross-regional variation

[9] We assume that each pardoned inmate returns to their province of residence prior to their current incarceration.

can be used to generate alternative estimates of the reverse incapacitation effect that can be compared to the results from our national level time series analysis.

Table 6 reports the results from a series of bivariate regressions. For each crime rate (the total crime rate and the twelve individual crime rates) we regress several alternative measures of the pre-post change in crime rates against the number of pardon inmates per 100,000 returned to each of the 103 provinces. The first column of results uses the crime rate change between July 2006 and September 2006 as the dependent variable. The next column uses the change in the average crime rate from June/July (the pre-period) to September/October (the post period). The third column adds May to the average for the pre period and November to the average for the post period while the final column uses the change in average crime rates from April through July to September through December. Since each regression includes a constant term the incapacitation effect is identified by cross-regional variation in the number of pardoned inmates per 100,000 above and beyond the overall national change. To facilitate comparison with our national estimates, we annualize the incapacitation effect by multiplying by twelve. Of course, the standard errors are adjusted accordingly.

The bivariate regression results for total crime yield estimates of annual incapacitation effects that are generally consistent with the results from the time series analysis. The models based on the change in crime between July and September and the change in crime for the average of the two months prior and the two months following the pardon yield the largest estimates of roughly 13.5 crimes per inmate per year. Our national level estimates based on the discontinuous break in crime yielded annual incapacitation effects of 14.4 to 17.9 crimes per year. Given the size of the standard errors reported in Tables 3 and 6, these two sets of estimates generally lie within each other’s confidence intervals. The cross-regional estimates based on the

change in three and four month averages are somewhat smaller (10.9 and 9.5 respectively). This is not surprising however, since the incarceration rate begins to climb fairly quickly and hence part of the prisoner release has been undone in these later months. All four of the cross-regional reverse incapacitation effect estimates for total crimes are statistically significant at the one percent level of confidence.

Regarding the results for the individual offenses there are some similarities to the national level analysis, yet some notable differences. We find consistently significant positive effects of receiving pardoned inmates on theft and robbery. All estimates for these crimes are significant at the one percent level of confidence. The point estimates for robbery are similar in magnitude to the point estimates from our national level analysis. The point estimates for theft however are considerably smaller. We find some evidence of a statistically significant increase in non-sexual violent crime in provinces receiving relatively high numbers of pardoned inmates. The annualized effects are more precisely measured when we average the pre and post-pardon crime rates in constructing the change in provincial crime rates, and consequently have lower p-values. We also find evidence of statistically significant reverse incapacitation effects for the offenses of extortion, vandalism, drugs/contraband, and other crimes.

As a final robustness check, we return to the national level time series and test whether the data itself reveals statistically significant structural breaks that correspond in time to the August 2006 pardon. Specifically, for total crime and for each of the individual twelve crime series, we estimate a series of regressions where the dependent variable is the national monthly crime rate and the explanatory variables are a linear and quadratic time trend, a dummy variable measuring a temporal structural break and interaction terms between the structural break dummy and the two trend variables. We allow the timing of the break dummy to vary across models for

each month from June 2004 through July 2008 yielding 48 models in all. We use each regression to test the significance of the structural break term and the two interaction terms with the linear time trend and identify the model that yields the maximum value for the Wald statistic from these tests.

The first column of Table 7 reports the maximum Wald statistic from this analysis for each crime rate while the second column reports the month (measured relative to August 2006) where the data reveal a structural break (i.e., the month yielding the maximum Wald statistic). Note, in our analysis in the previous section of national level time series we pre-specify the structural break to occur at t=1. For the total crime rate, the theft rate, and the robbery rate, the data reveal structural breaks starting in September 2006 (corresponding to t=1). For extortion, soliciting a prostitute, and other crime, the data reveal structural breaks in August 2006. For all remaining crimes, the data indicate that the months yielding the largest Wald statistics occur substantially prior to the collective pardon.

To draw inference regarding the significance of the identified structural breaks, we employ several strategies. First, we use the asymptotic critical values from Andrews (1993). These are based on tests for structural breaks of three parameters where ten percent of the data are trimmed from the beginning and end of the time period. We also generate critical values based on Monte Carlo simulations following the analysis in Piehl et. al. (2003). Specifically, for each crime we fit a regression of the crime rate on a linear and quadratic time trend and estimate the residual variance (effectively assuming no structural break in the data). We then use these parameters to simulate 10,000 data sets assuming normal iid error terms with a variance equal to the empirical estimate from the true time series. We apply the structural break estimator to each simulated data set, generating 10,000 estimates of the max-Wald statistic, and then take the value

of this statistic at the 99 percentile. This serves as our critical value against which we compare the test statistic calculated from the actual data set. We also perform similar Monte Carlo experiments where the regression used to generate the 10,000 data sets fits an AR1 process to the underlying data. The Andrews critical values are reported in the third column while our simulated critical values are reported in the fourth column (assuming iid errors) and the fifth column (assuming the error term follows an AR1 process).

The max-Wald statistics for total crime, theft, and robbery far exceed all three critical values. Moreover, as the timing of the structural breaks correspond exactly to the timing of the pardon, this exercise yields strong evidence of an impact of the pardon on these crime rates. For the three crime rates with structural breaks in August 2006 (extortion, prostitution, and other crimes) the test statistic exceed all three critical values.

6. Conclusion

We document sizable increases in crime associated with the August 2006 Italian collective pardon. Relative to the number of inmates released, our various estimation strategies suggest that each prison-year served, at current Italian incarceration rates, prevents between 13 and 28 crimes reported to the police. Most of this impact is attributable to thefts of various sorts, and to a lesser degree, robbery. However, we find some evidence that the pardon may have lead to a slight increase in violent crime as well. Our empirical estimates, based on three separate sources of variation created by the pardon, are generally consistent with one another. In addition, more general tests for structural instability in crime rates that do not pre-specify the timing of structural change confirm our main findings.

The collective pardon presents an unusual research opportunity in that the variation induced by the pardon created crime deterrence and incapacitation effects that offset one another. This is in contrast to variation in incarceration caused by sentencing reform that induces deterrence and incapacitation effects in the same direction. This particular fact permits us to interpret our estimates as lower-bound incapacitation effects. To be sure, we do not have a large body of estimates of joint deterrence/incapacitation effects for Italy against which we can compare our results. The research by Barbarino and Mastrobuoni (2009) analyzing the effects of earlier pardons and amnesties identified lower-bound incapacitation effects similar to ours, while the study by Drago, Galbiati, and Vertova (2009) analyzes deterrence among pardoned inmates.

However, we can and do compare our estimates to estimates of pure incapacitation effects and joint-deterrent/incapacitation effects based on U.S. data. Our estimates for Italy lie within the range of estimates from older survey research estimates of pure incapacitation conducted during a time period when the U.S. incarceration rate was much closer to Italy's current rate (and much lower than the current U.S. rate). Our estimates are also similar in magnitude to the findings from joint incapacitation/deterrence effect estimates based on U.S. state panel data for relatively earlier time periods. Together these findings suggest that most of the crime-preventing effects of incarceration operate through incapacitation rather than deterrence.

To be sure, there are several qualifications that should be kept in mind when comparing our estimates to the United States. First, crime characterization and the propensity to report to the police may differ between the two countries. Second, while we make comparisons against estimates for the U.S. based on relatively early time periods (the 1980s and early 1990s), the incarceration rate in the U.S. during these periods is still roughly double that of Italy's current

rate. Given the extant evidence of decreasing returns to scale in crime-incarceration effect (Johnson and Raphael 2010, Liedka, Piehl and Useem 2006), these comparisons may overstate the relative importance of incapacitation.

The findings from the current study also validate the identification strategy employed earlier in Johnson and Raphael (2010) that exploits variation along the dynamic adjustment path of incarceration between steady-state values. As sharp changes in incarceration rate akin to what we study here are relatively rare, researchers seeking to identify exogenous variation in incarceration for studying effects on crime, public budgets, and other outcomes should pay greater attention to the underlying dynamic processes driving incarceration rates.

A final caveat to interpreting these results concerns the fact that we are clearly estimating a local average treatment effect. The ultimate impact of releasing inmates on crime most certainly depends on which inmates are released, the degree of post-release supervision via community corrections, the degree to which police in receiving communities are able to handle the inflow (are not overburdened by current workloads), programming that released inmates undergo while incarcerated, as well as a number of other factors. In addition, as we have mentioned several times throughout the paper incapacitation effects most certainly depends on the scale of incarceration, with great expansions in the use of incarceration along the extensive margin of the criminally active population most certainly netting less serious criminals. The results here suggest that an Italian incarceration rate of 60 per 100,000 in Italy is likely to be low and that the bang-per-buck (crimes prevented per euro spent on corrections) was quite high in the aftermath of the 2006 pardon. In fact, that cost-benefit analysis presented in Barbarino and Mastrobuoni (2009) suggest that this was the case after most pardons in Italy occurring during the post-war period. Similar arguments were probably applicable to the U.S. during the 1970s,

when the incarceration rate stood at 110 per 100,000. However, extrapolating our results from Italy to the current situation in the U.S. is unwise. With a 2009 U.S. incarceration rate of 502 per 100,000, underlying correctional conditions are too different to make such comparisons.

References

Andrews, Donald W. K. (1993), "Tests for Parameter Instability and Structural Change With Unknown Change Points," *Econometrica*, 61(4): 821-856.

Angrist, Joshua D. and Jörn-Steffen Pischke (2009), *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton University Press: Princeton, NJ.

Barbarino, Alessandro and Giovanni Mastrobuoni (2009), "The Incapacitation Effect of Incarceration: Evidence from Several Italian Collective Pardons," Working Paper.

Becker, Gary S. (1968), "Crime and Punishment: An Economic Approach," *Journal of Political Economy*, 76: 169-217.

Drago, Francesco; Galbiati, Roberto and Pietro Vertova (2009), "The Deterrent Effects of Prison: Evidence from a Natural Experiment," *Journal of Political Economy*, 117(2): 257-280.

Johnson, Rucker and Steven Raphael (2010), "How Much Crime Reduction Does the Marginal Prisoner Buy?" Working Paper, UC Berkeley.

Kessler, Daniel and Steven D. Levitt (1999), "Using Sentence Enhancements to Distinguish Between Deterrence and Incapacitation," *Journal of Law and Economics*, 42(1): 343-363.

Lee, David S. and Justin McCrary (2009), "The Deterrent Effect of Prison: Dynamic Theory and Evidence," Industrial Relations Section Working Paper #11491, Princeton University.

Levitt, Steven D. (1996), "The Effect of Prison Population Size on Crime Rates: Evidence from Prison Overcrowding Legislation," *Quarterly Journal of Economics*, 111(2): 319-351.

Levitt, Steven D. (1998), "Juvenile Crime and Punishment," *Journal of Political Economy*, 106(6): 1156-1185.

Liedke, Raymond; Piehl, Anne Morrison and Bert Useem (2006), "The Crime Control Effect of Incarceration: Does Scale Matter?" *Criminology and Public Policy*, 5: 245-275.

Ludwig, Jens and Thomas J. Miles (2007), "The Silence of the Lambdas: Deterring Incapacitation Research," *Journal of Quantitative Criminology,* 23: 287-301.

Marvell, Thomas and Carlysle Moody (1994), "Prison Population Growth and Crime Reduction," *Journal of Quantiative Criminology,* 10: 109-140.

Owens, Emily G. (2009), "More Time, Less Crime? Estimating the Incapacitative Effects of Sentence Enhancements" *Journal of Law and Economics, 52(3) 551-579, 2009.*

Piehl, Anne Morrison; Cooper, Suzanne J.; Braga, Anthony A. and David M. Kennedy (2003), "Testing for Structural Breaks in the Evaluation of Programs," *Review of Economics and Statsitics*, 85(3): 550-558.

Polinsky, A. Mitchell and Steven Shavell (1984), "The Optimal Use of Fines and Imprisonment," *Journal of Public Economics*, 24: 89-99.

Spelman, William (1994), *Criminal Incapacitation*, Plenum Press: New York.

Spelman, William (2000), "What Recent Studies Do (and Don't) Tell Us About Imprisonment and Crime," in Michael Tonry (ed.) *Crime and Justice: A Review of the Research,*University of Chicago Press: Chicago, 27: 419-494

Webster, Cheryl M.; Doob, Anthony N.; and Franklin E. Zimring (2006), "Proposition 8 and Crime Rates in California: The Case of the Disappearing Deterrent," *Criminology and Public Policy,* 5(3): 417-448.

Figure 1: Scatter Plot of Monthly Incarceration Rate Against Month Measured Relative to August 2006

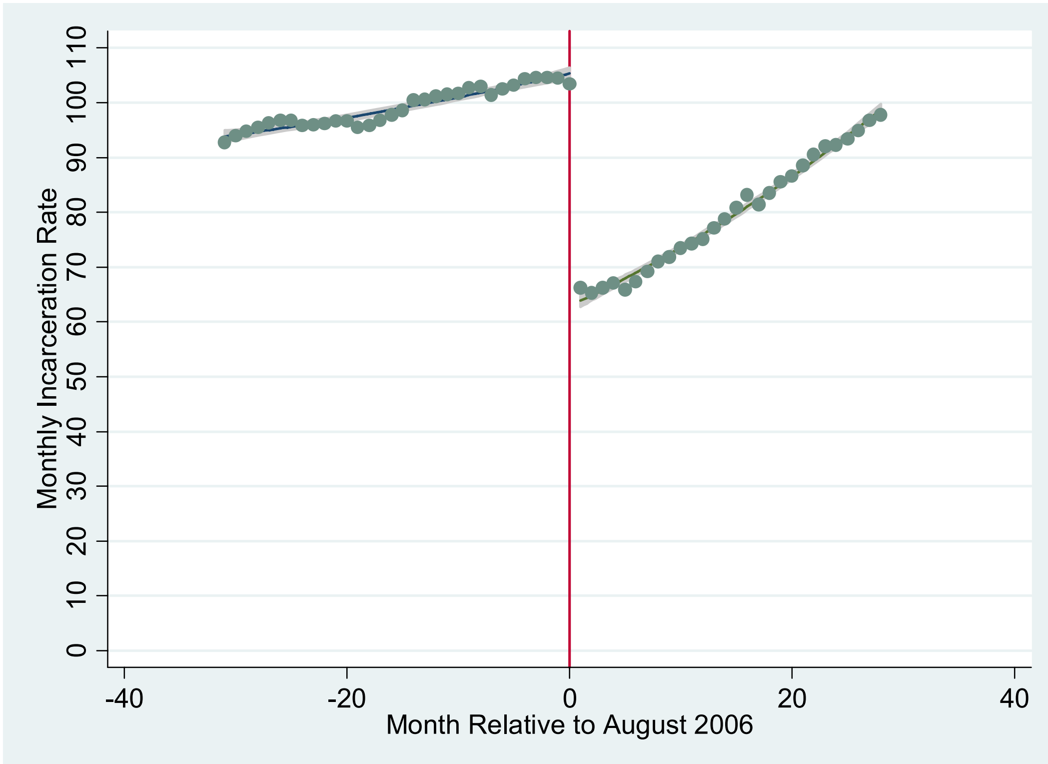

Figure 2: Scatter Plot of Total Monthly Crimes per 100,000 Italian Residents Against Month Measured Relative to August 2006

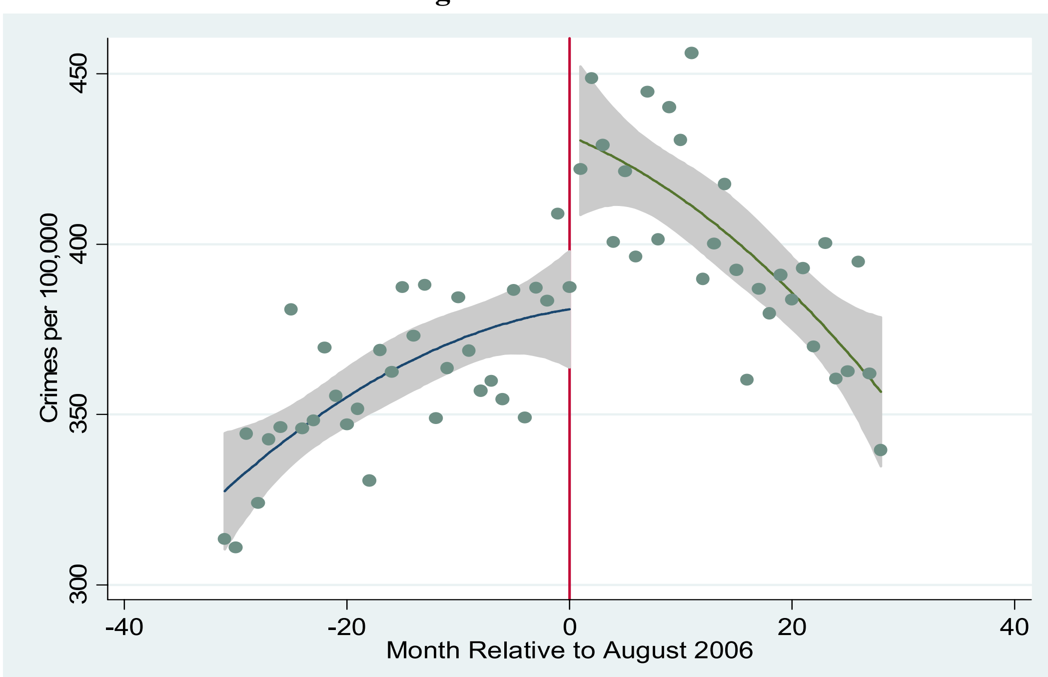

Figure 3: Scatter Plot of Total Non-Sexual Violent Crimes per 100,000 Italian Residents Against Month Measured Relative to August 2006

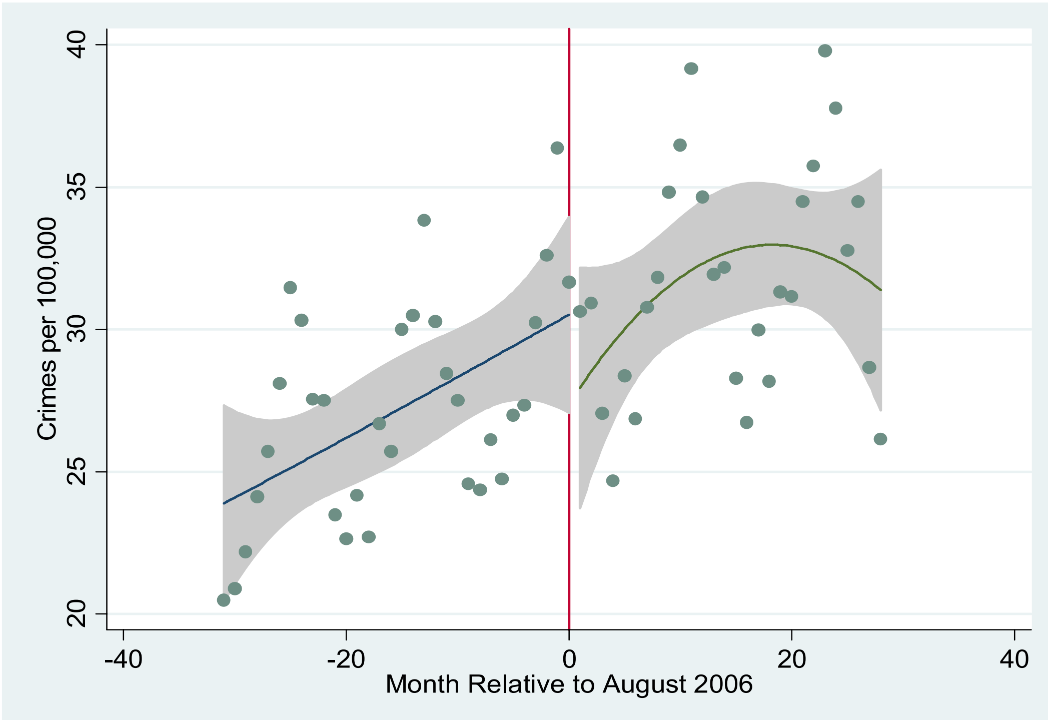

Figure 4: Scatter Plot of Sexual Assault and Corruption of Minor Offenses per 100,000 Italian Residents Against Month Measured Relative to August 2006

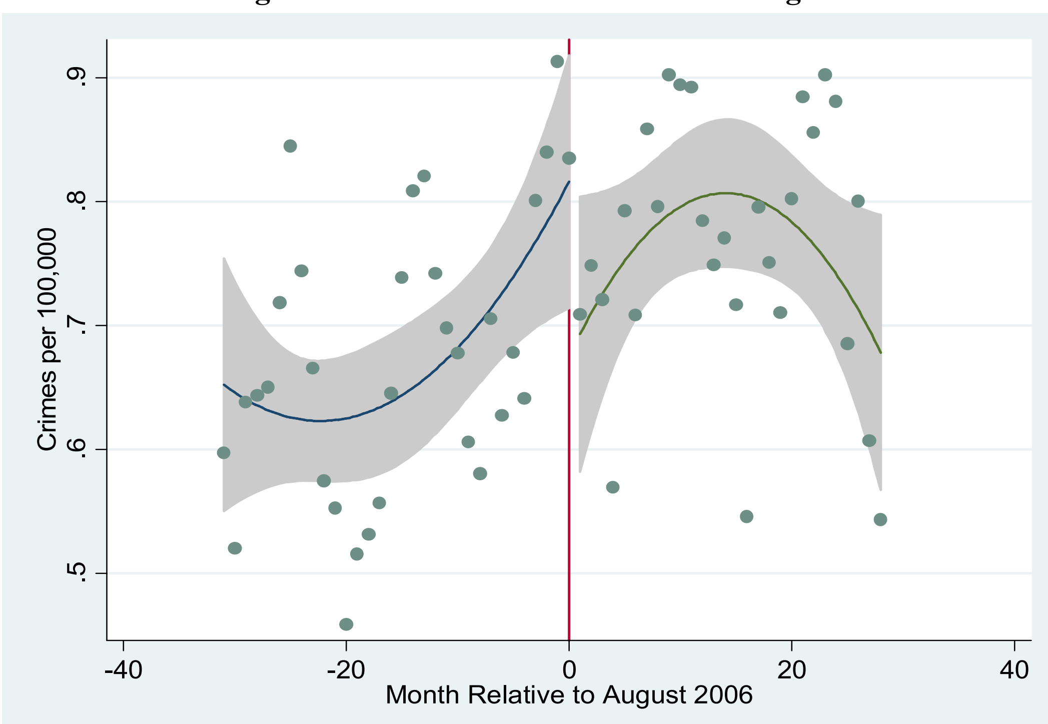

Figure 5: Scatter Plot of Thefts/Receiving Stolen Property Offenses per 100,000 Italian Residents Against Month Measured Relative to August 2006

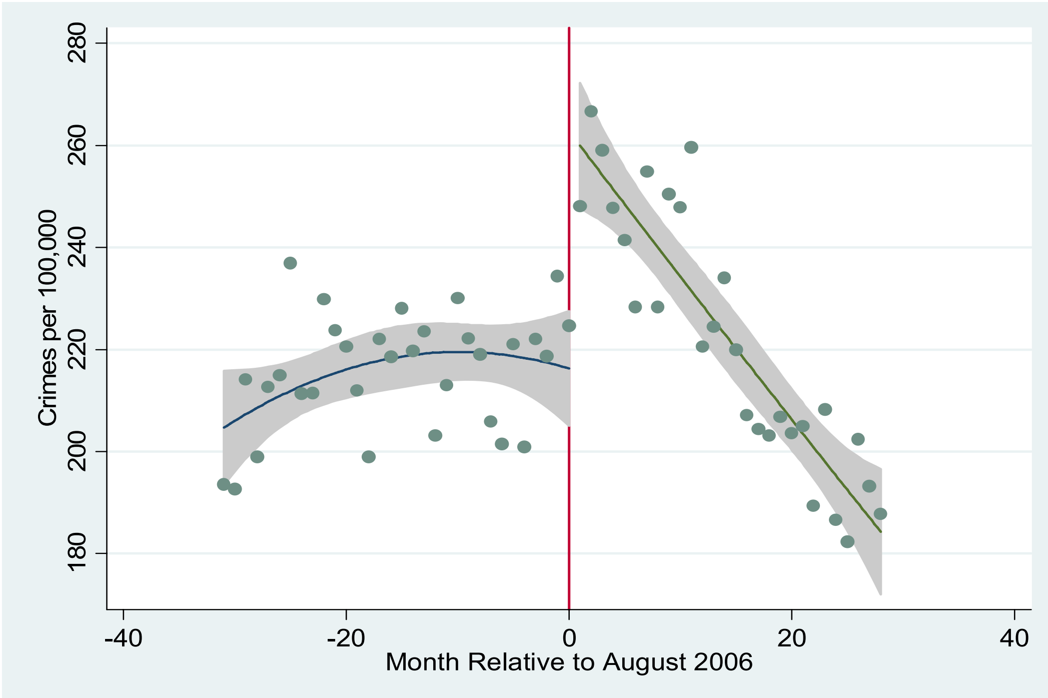

Figure 6: Scatter Plot of Robberies per 100,000 Italian Residents Against Month Measured Relative to August 2006

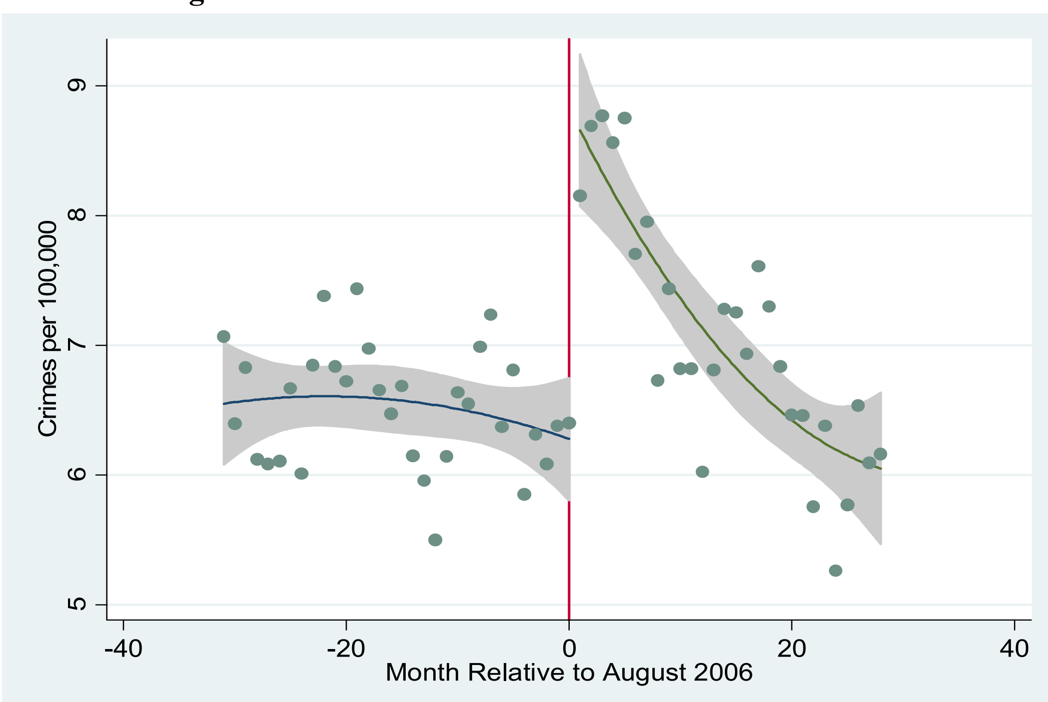

Figure 7: Scatter Plot of Extortion/Usury/Money Laundering Crimes per 100,000 Italian Residents Against Month Measured Relative to August 2006

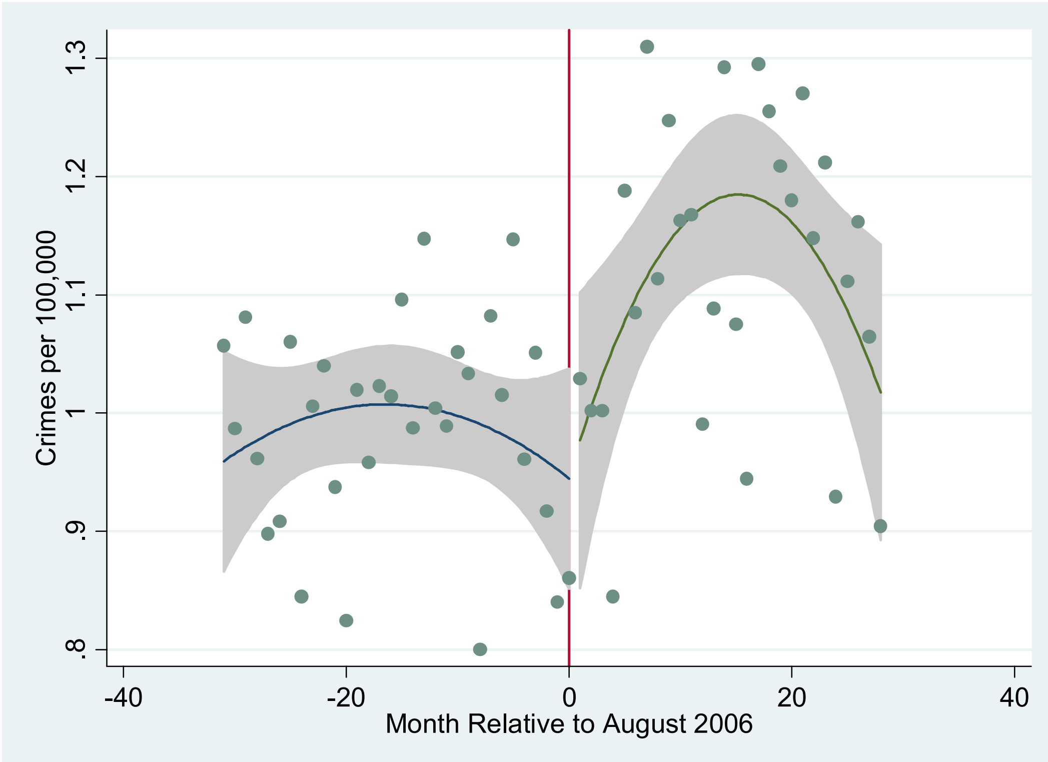

Figure 8: Scatter Plot of Kidnappings per 100,000 Italian Residents Against Month Measured Relative to August 2006

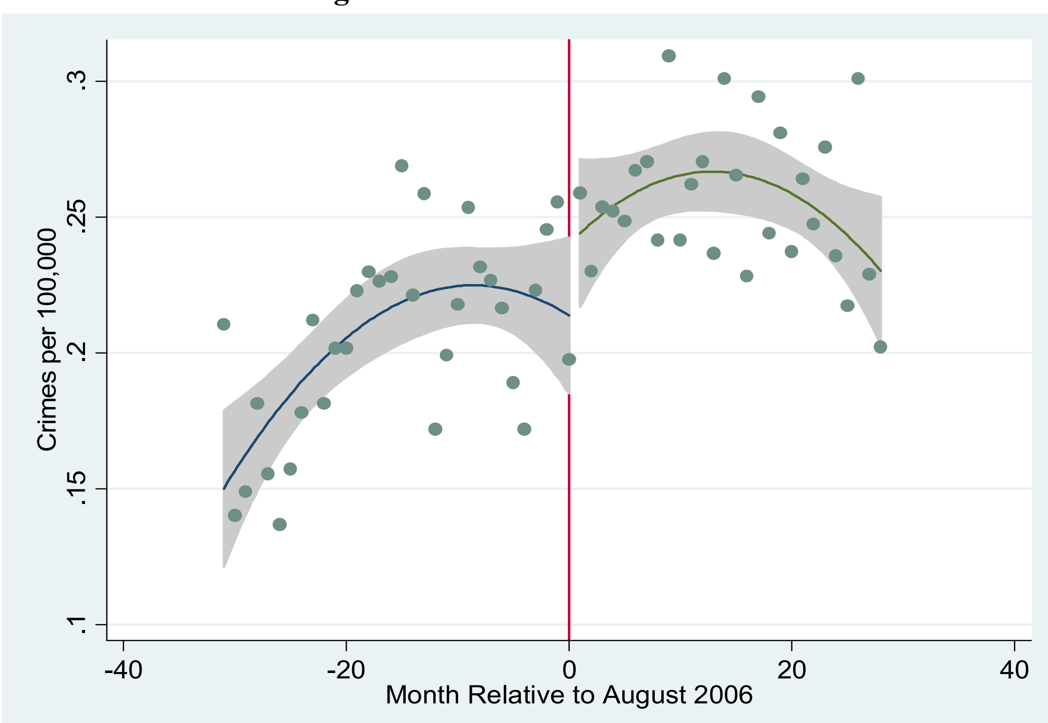

Figure 9: Scatter Plot of Arson Crimes per 100,000 Italian Residents Against Month Measured Relative to August 2006

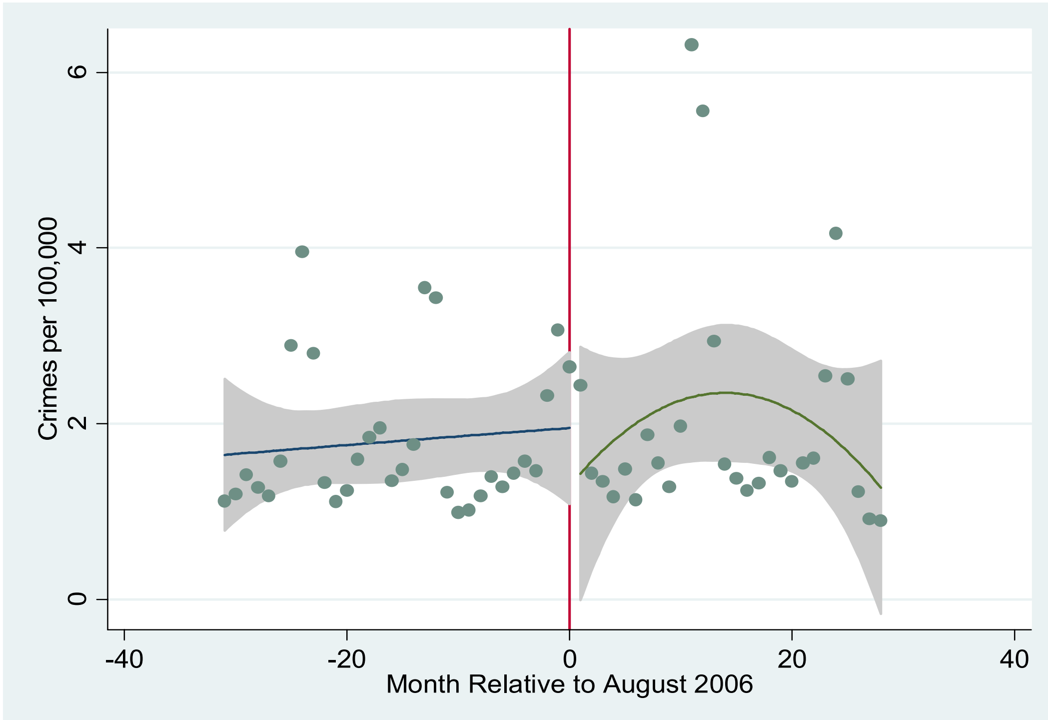

Figure 10: Scatter Plot of Vandalism Crimes per 100,000 Italian Residents Against Month Measured Relative to August 2006

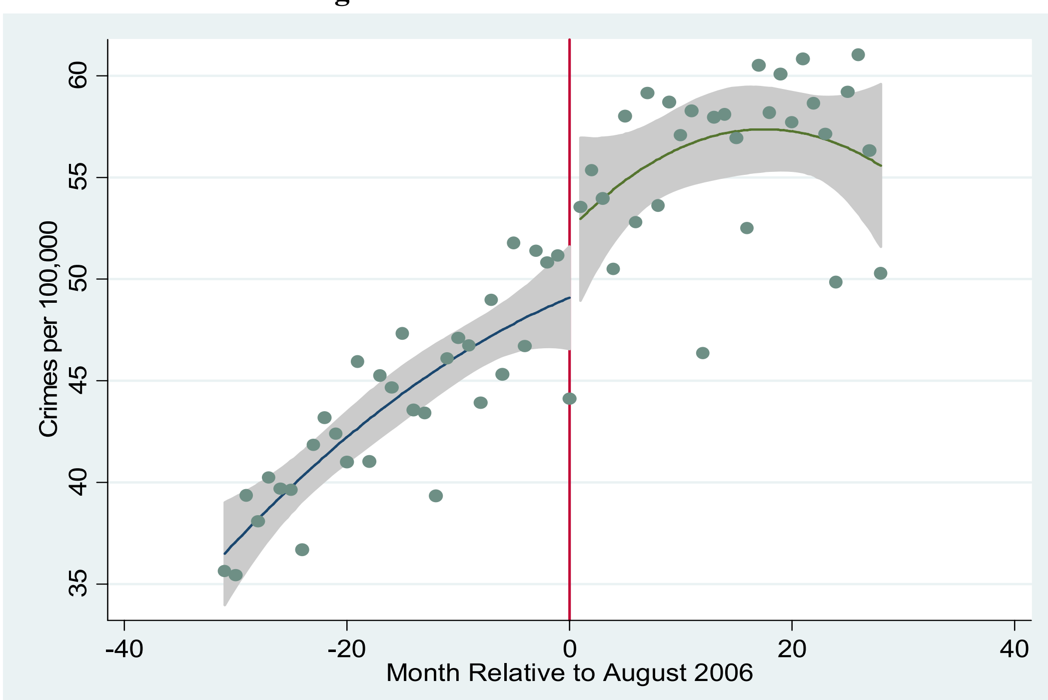

Figure 11: Scatter Plot of Drugs/Contraband Crimes per 100,000 Italian Residents Against Month Measured Relative to August 2006

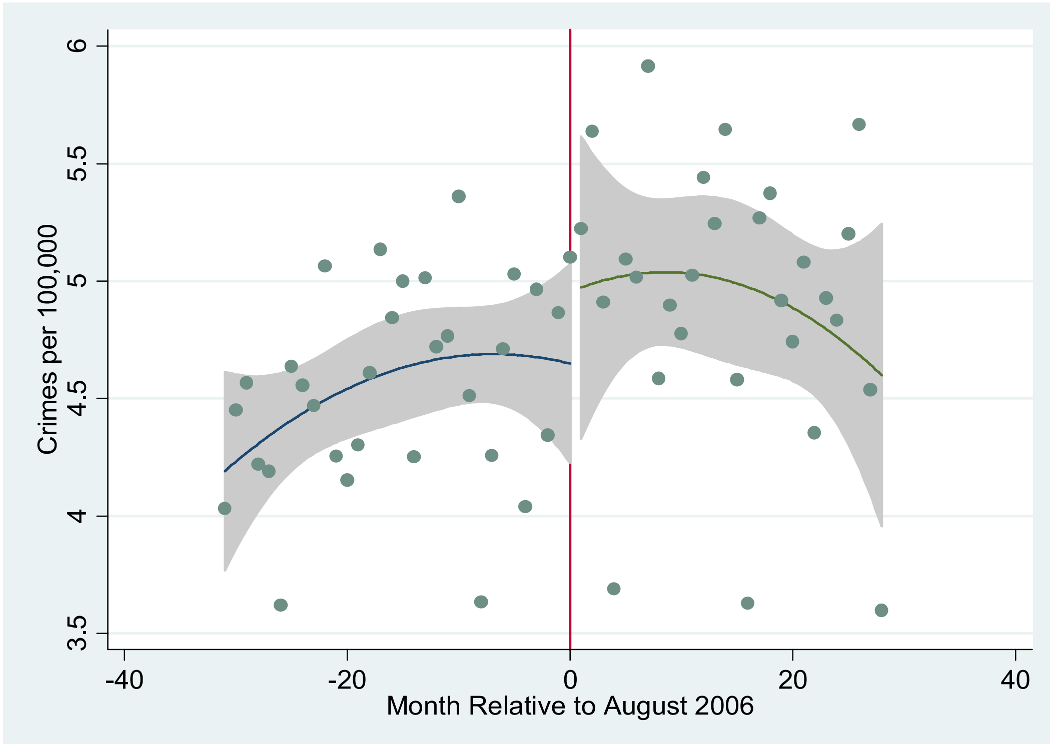

Figure 12: Scatter Plot of Soliciting a Prostitute Crimes per 100,000 Italian Residents Against Month Measured Relative to August 2006

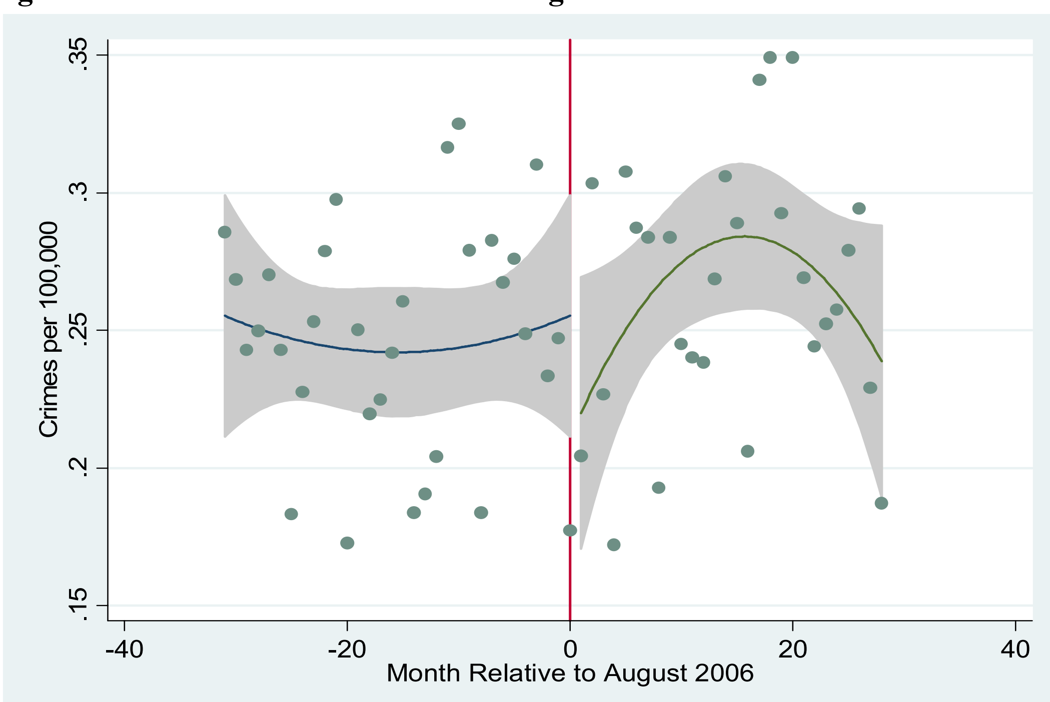

Figure 13: Figure 8: Scatter Plot of Other Crimes per 100,000 Italian Residents Against Month Measured Relative to August 2006

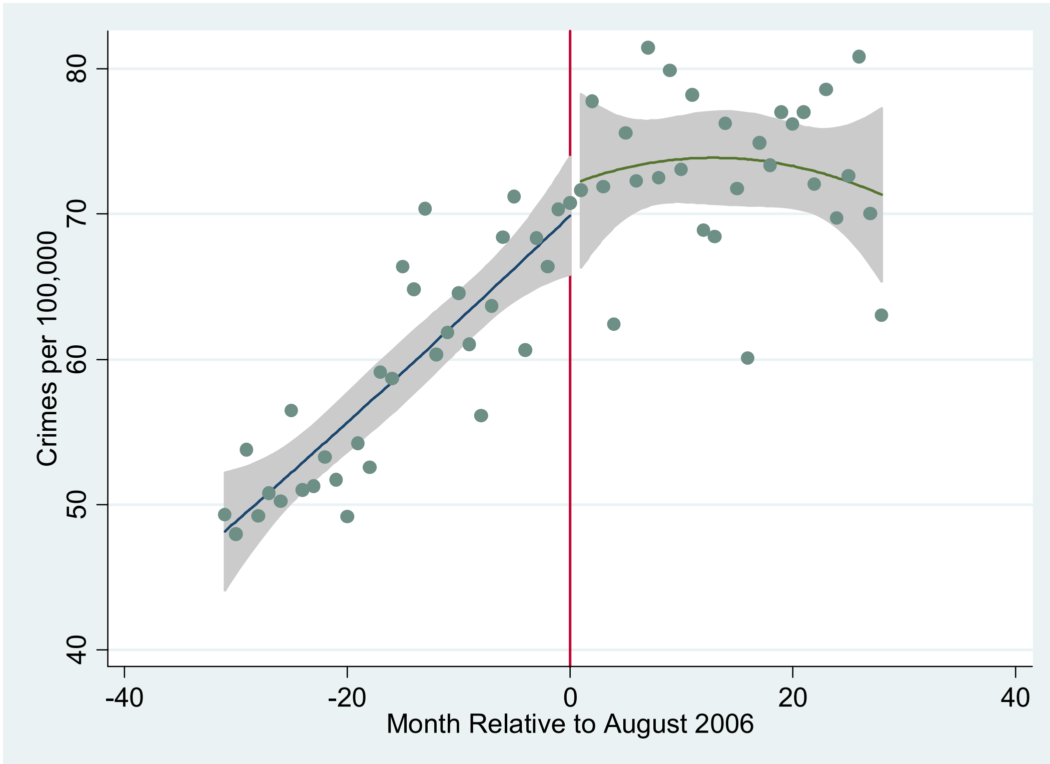

Table 1
Italian Crime Rates (Incidents per 100,000) by Year and by Offense Type

Crime Type	Crime Rate 2004 through 2008 Combined	Percent of total crime	Crime Rates by Year				
			2004	2005	2006	2007	2008
Total Crime	378.41	100%	344.08	365.37	393.07	412.56	376.98
Non-sexual violent crime	29.25	7.73%	25.37	27.39	29.11	31.84	32.54
Sexual assault/corruption of minor	0.72	0.19%	0.63	0.66	0.73	0.78	0.77
Thefts/receiving stolen property	218.51	57.74%	213.38	217.5	229.21	234.74	197.71
Robbery	6.77	1.79%	6.59	6.51	7.14	7.21	6.39
Extortion/usury/ money laundering	1.05	0.28%	0.97	1.01	0.98	1.14	1.15
Kidnapping	0.23	0.06%	0.18	0.23	0.23	0.26	0.25
Arson	1.89	0.50%	1.76	1.78	1.80	2.35	1.76
Vandalism	49.51	13.08%	39.43	44.54	50.30	55.79	57.49
Drugs/contraband	4.72	1.25%	4.35	4.68	4.73	4.99	4.88
Soliciting a prostitute	0.25	0.07%	0.25	0.24	0.25	0.26	0.28
Other crime	65.51	17.31%	51.17	60.83	68.61	73.18	73.77

Table 2
Regressions of Total Monthly Crime Rates (Panel A) and Incarceration Rates (Panel B) on a Quadratic Trend with Post-Pardon Breaks in Intercept and Trend Coefficients

Panel A: Dependent Variable=Total Monthly Crimes per 100,000 Residents

	(1)	(2)	(3)	(4)
Time	0.500	0.196	0.986	1.107
	(1.365)	(0.690)	(1.078)	(1.439)
$Time^2$	-0.039	-0.045	-0.44	-0.041
	(0.042)	(0.022)	(0.031)	(0.043)
Post-pardon	50.861	59.247	58.085	57.016
	(14.451)	(7.710)	(7.646)	(11.571)
Time*post-	-1.842	-2.290	-4.891	-4.967
pardon	(2.242)	(1.104)	(1.825)	(2.433)
$Time^2$*post-	-0.008	0.019	0.060	0.055
pardon	(0.073)	(0.039)	(0.051)	(0.067)
Month effects	No	Yes	Yes	Yes
Year Effects	No	No	Yes	Yes
AR1 Correction	No	No	No	Yes
R^2	0.711	0.945	0.951	-
N	60	60	60	60

Panel B: Dependent Variable=Monthly Incarceration Rate

	(1)	(2)	(3)	(4)
Time	0.465	0.504	0.499	0.224
	(0.078)	(0.070)	(0.109)	(0.221)
$Time^2$	0.003	0.005	0.005	-0.001
	(0.002)	(0.002)	(0.003)	(0.009)
Post-pardon	-42.405	-42.782	-42.699	-38.116
	(0.824)	(0.785)	(0.769)	(3.502)
Time*post-	0.474	0.489	0.680	0.501
pardon	(0.127)	(0.112)	(0.184)	(0.411)
$Time^2$*post-	0.009	0.005	-0.002	0.018
pardon	(0.004)	(0.004)	(0.005)	(0.012)
Month effects	N	Y	Y	Y
Year Effects	N	N	Y	Y
AR1 Correction	N	N	N	Y
R^2	0.993	0.994	0.997	-
N	60	60	60	60

Standard errors are in parentheses.

Table 3
Estimates of Annualized Incapacitation Effects Using the Pre-Post Pardon Break in Crime and Incarceration and Using Varying Along The Dynamic Adjustment Path

	Identification using break in time series	Identification using variation along the dynamic adjustment path measured at…			
		T=6	T=12	T=18	T=24
Model (1)	14.392[a]	21.503[c]	25.938[a]	36.354[a]	46.783[a]
	(4.104)	(11.495)	(5.925)	(8.023)	(16.202)
Model (2)	16.618[a]	24.550[a]	26.419[a]	33.432[a]	36.808[a]
	(2.010)	(4.780)	(2.437)	(4.389)	(7.537)
Model (3)	16.324[a]	26.962[a]	26.816[a]	30.681[a]	29.819[a]
	(2.001)	(5.600)	(2.964)	(4.787)	(7.381)
Model (4)	17.950[a]	28.919[a]	27.151[a]	28.085[a]	24.650[b]
	(3.999)	(10.023)	(5.489)	(8.122)	(10.544)

Standard errors are in parentheses. Model specifications correspond to the model specification used in Table 2. All figures are annualized to approximate the incapacitation effect of a person-year of prison time. The standard error estimates for models (1) through (3) identifying with the break in the time series are calculated by taking the standard error from a two-stage least squares regression of total crime rates on incarceration rates with the first-stage specifications corresponding to Panel B in Table 2 and the second stage specification including all variables in the models in Panel A of Table 2 with the exception of the post variable and the addition of the incarceration rate (i.e., the post variable serves as the instrument). For all estimates using Model (4) and all estimates identifying the incapacitation effect off the dynamic adjustment of crime and incarceration to the collective pardon, we first estimate the linear combination of parameters and the accompanying standard errors given in equations (18) and (19) in the text. We then estimate the standard error of the ratio giving the incapacitation effect by the delta method. We assume that the covariance between the two components of each ratio equals zero.
a. Statistically significant at the one percent level of confidence.
b. Statistically significant at the five percent level of confidence.
c. Statistically significant at the 10 percent level of confidence.

Table 4
Regression Estimates of Discontinuity in Crime Rates for Individual Offenses

Offense	Base specification	Base specification plus month effects	Base specification plus month and year effects	Base specification plus month and year effects with AR1 correction
Total Crime	50.861 (14.451)[a]	59.247 (7.710)[a]	58.085 (7.646)[a]	57.016 (11.571)[a]
Non-sexual violent crime	-3.168 (2.851)	1.446 (0.751)[c]	1.498 (0.734)[b]	1.510 (1.370)
Sexual assault/corruption of minor	-0.141 (0.079)[c]	0.010 (0.040)	-0.001 (0.038)	0.000 (0.053)
Thefts/receiving stolen property	46.564 (8.771)[a]	45.957 (5.547)[a]	45.246 (5.569)[a]	41.503 (6.893)[a]
Robbery	2.551 (0.392)[a]	2.019 (0.249)[a]	2.0669 (0.238)[a]	2.002 (0.281)[a]
Extortion/usury/ money laundering	0.002 (0.081)	0.046 (0.053)	0.035 (0.054)	0.035 (0.053)
Kidnapping	0.026 (0.021)	0.027 (0.022)	0.020 (0.023)	0.018 (0.019)
Arson	-0.667 (0.861)	0.412 (0.487)	0.538 (0.483)	0.767 (0.952)
Vandalism	3.311 (2.437)	2.308 (1.281)[c]	2.459 (1.209)[b]	2.575 (3.183)
Drugs/contraband	0.305 (0.397)	0.390 (0.219)[c]	0.327 (0.220)	0.338 (0.270)
Soliciting a prostitute	-0.044 (0.035)	-0.071 (0.025)[a]	-0.072 (0.024)[a]	-0.076 (0.020)[a]
Other crime	2.123 (3.731)	6.703 (2.301)[a]	5.967 (2.310)[a]	5.243 (3.613)

Standard errors are in parentheses. The base specification includes a time trend, a time trend squared, a dummy for the post-pardon period, and interaction terms between the post-pardon dummy and the time and time-squared terms. The coefficients in the tables are the coefficients on the post-pardon dummy.
a. Statistically significant at the one percent level of confidence.
b. Statistically significant at the five percent level of confidence.
c. Statistically significant at the 10 percent level of confidence.

Table 5
Estimates of Annualized Incapacitation Effects for All Crimes and For Individual Offenses Using the Pre-Post Pardon Break in Crime and Incarceration and Using Varying Along The Dynamic Adjustment Path

Offense	Identification using break in time series	Identification using variation along the dynamic adjustment path measured at…			
		T=6	T=12	T=18	T=24
Total Crime	17.950[a]	28.919[a]	27.151[a]	28.085[a]	24.650[b]
	(3.999)	(10.023)	(5.489)	(8.122)	(10.544)
Non-sexual violent crime	0.475	-0.789	-0.383	-0.099	0.111
	(0.789)	(1.669)	(0.764)	(0.499)	(0.795)
Sexual assault corruption of minor	0.000	0.073	0.068[b]	0.064[b]	0.062
	(0.017)	(0.058)	(0.027)	(0.024)	(0.037)
Thefts/receiving stolen property	13.066[a]	43.586[a]	33.719[a]	26.806[a]	21.693[a]
	(2.480)	(13.207)	(6.744)	(5.963)	(7.455)
Robbery	0.630[a]	1.258[b]	1.093[a]	0.978[a]	0.892[a]
	(0.106)	(0.497)	(0.224)	(0.200)	(0.304)
Extortion/usury/ money laundering	0.011	-0.104	-0.016	0.046	0.091
	(0.017)	(0.088)	(0.036)	(0.053)	(0.083)
Kidnapping	0.006	-0.022	0.002	0.018	0.031
	(0.006)	(0.031)	(0.014)	(0.014)	(0.021)
Arson	0.241	-0.672	-0.246	0.052	0.273
	(0.301)	(1.495)	(0.600)	(0.816)	(1.321)
Vandalism	0.811	-3.306	-0.747	1.046	2.372[c]
	(1.005)	(2.122)	(0.980)	(0.854)	(1.257)
Drugs/contraband	0.106	0.332	0.281[c]	0.246[c]	0.219
	(0.086)	(0.325)	(0.155)	(0.144)	(0.214)
Soliciting a prostitute	-0.024[a]	-0.052	0.003	0.042[a]	0.071[a]
	(0.007)	(0.036)	(0.016)	(0.014)	(0.022)
Other crime	1.651	5.297	2.894	1.211	-0.034
	(1.148)	(4.118)	(1.816)	(1.862)	(2.894)

Standard errors are in parentheses. All estimates are based on specification in model (4) of Table 2.. All figures are annualized to approximate the incapacitation effect of a person-year of prison time. To estimate standard errors for the annualized incapacitation effects, we first estimate the linear combination of parameters and the accompanying standard errors given in equations (18) and (19) in the text. We then estimate the standard error of the ratio giving the incapacitation effect by the delta method. We assume that the covariance between the two components of each ratio equals zero.
a. Statistically significant at the one percent level of confidence.
b. Statistically significant at the five percent level of confidence.
c. Statistically significant at the 10 percent level of confidence.

Table 6
Estimates of Annualized Incapacitation Effects Based on Bivariate Regression of the Change in Crime Rates Measured at the Province Level Against the Number of Inmates from the Province That Were Pardoned

Offense	Change, July to September	Change, June-July to September-October	Change, May-July, to September-November	Change, April-July to September-December
Total Crime	13.548[a]	13.653[a]	10.933[a]	9.463[a]
	(3.404)	(2.810)	(2.324)	(2.042)
Non-sexual violent	0.076[c]	0.080[b]	0.068[a]	0.054[b]
crime	(.045)	(0.033)	(0.026)	(0.022)
Sexual assault	-0.021[b]	0.002	0.003	0.003
corruption of minor	(0.011)	(0.007)	(0.006)	(0.005)
Thefts/receiving	3.691[a]	3.987[a]	3.225[a]	2.958[a]
stolen property	(1.240)	(1.030)	(0.874)	(0.782)
Robbery	0.814[a]	0.995[a]	0.855[a]	0.806[a]
	(0.086)	(0.088)	(0.075)	(0.069)
Extortion/usury/	0.060[a]	0.041[a]	0.028[a]	0.023[a]
money laundering	(0.013)	(0.009)	(0.007)	(0.006)
Kidnapping	-0.004	0.001	0.005	0.008
	(0.016)	(0.011)	(0.009)	(0.008)
Arson	0.069	0.096	0.090	0.117[b]
	(0.140)	(0.092)	(0.064)	(0.046)
Vandalism	0.532[b]	0.386[b]	0.326[b]	0.252[b]
	(0.247)	(0.183)	(0.140)	(0.119)
Drugs/contraband	0.218[a]	0.148[a]	0.097[b]	0.054[c]
	(0.059)	(0.042)	(0.037)	(0.030)
Soliciting a prostitute	-0.011	0.000	0.000	0.007
	(0.015)	(0.013)	(0.012)	(0.010)
Other crime	0.481[a]	0.402[a]	0.300[a]	0.218[a]
	(0.118)	(0.102)	(0.081)	(0.071)

Figures in the table come from bivaraite regressions of the province-level change in crime rates on the number of pardoned inmates from the province expressed per 100,000 province residents. All regressions are weighted by province population. The figures in the table are annualized by multiplying the monthly effect by twelve. Standard errors (in parentheses) are adjusted accordingly. The dependent variable in the first column is the change in the crime rate between July and September 2006. The second column calculated the change in the average monthly crime rate for June through July to September through October. The third column averages the three months prior and three months following the pardon while the fourth column calculates the change in crime rates using four-month averages.

a. Statistically significant at the one percent level of confidence.
b. Statistically significant at the five percent level of confidence.
c. Statistically significant at the ten percent level of confidence

Table 7
Results from Tests for Structural Change with Unknown Break Dates

Offense	Maximum Wald Statistics	Identified month of break measured related to August 2006 (August 2006 set to zero)	Andrews Critical Value	99th Percentile of the Distribution of Max-Wald Stat. from Monte Carlos Simulations Assuming iid Errors	99th Percentile of the Distribution of Max-Wald Stat. from Monte Carlo Simulations Assuming AR1 Errors
Total Crime	196.56	1	18.28	16.77	43.45
Non-sexual violent crime	23.33	-19	18.28	18.07	19.08
Sexual assault corruption of minor	25.78	-22	18.28	25.60	27.29
Thefts/receiving stolen property	258.31	1	18.28	18.82	70.67
Robbery	180.74	1	18.28	23.84	58.63
Extortion/usury/ money laundering	32.10	0	18.28	18.36	24.66
Kidnapping	23.16	-12	18.28	18.45	20.49
Arson	22.09	-16	18.28	19.91	23.17
Vandalism	41.63	-3	18.28	12.40	14.93
Drugs/contraband	17.71	-13	18.28	16.91	16.50
Soliciting a prostitute	26.35	0	18.28	16.75	18.97
Other crime	44.35	0	18.28	20.16	23.30

Maximum Wald statistics comes from a series of regressions of the crime rate on a linear and quadratic time trend, a break dummy, and interaction terms between the two time trends and the break dummy. For each crime rate we estimate this regression 48 times allowing the break dummy to vary from 6 months from the start of the 60 month time series to 48 months into the time series. The maximum Wald statistic is the largest of the test statistics from these 48 regressions. To draw inference regarding the significance of the identified structural break, we use the asymptotic critical values from Andrews (1993). We also generate critical values based on Monte Carlo simulations following Piehl et. al. (2003). Specifically, for each crime we fit a regression of the crime rate on a linear and quadratic time trend and estimate the residual variance. We then use these parameters to simulate 10,000 data sets assuming normal iid error terms. We apply the structural break estimator to each simulated data set and then take the value of the max-Wald statistic at the 99 percentile. This serves as our critical value against which we compare the test statistic calculated from the actual data set. We also perform similar Monte Carlo experiments where the regression used to generate the 10,000 data sets fits an AR1 process to the underlying data.