Do Concealed Gun Permits Deter Crime? New Results From a Dynamic Model

Marjorie B. McElroy and Peichun Wang
Duke University and the University of Pennsylvania

November 8, 2012

Preliminary and incomplete. Please do not quote.

1 Introduction and Summary

Setting off a fifteen year controversy, Lott and Mustard [1997] famously argued that state laws providing for the liberal issue of concealed gun permits reduce violent crime. These laws are called shall issue laws (SILs) and they argued that these laws increase the probability that a would-be perpetrator's crime will fail because he is more likely to be threatened with a gun or shot by his intended victim. In this controversy the weapon of choice has been difference-in-difference estimates. We present and estimate a more general cohort panel data model (CPDM) of changes in the crime rate that accounts for forward-looking behaviors of potential and contemporaneous violent criminals. Treating violent crime as a career, the model decomposes the effects of SILs into a *direct effect* on entry decisions, a *surprise effect* on exit decisions, and a *selection effect* on those who entered violent crime under the aegis SILs. The CPDM shows how within a state, changes in the crime rate depend on the distribution of the population over generations whose "entry windows" contain the advent of SILs, precede SILs, or postdate SILs. The CPDM also shows how the evolution of changes in the crime rate evolve over time as younger cohorts replace older ones and the distribution of the population over these three generations evolves. Applying generalized least squares with autocorrelated errors to state-panel data on changes in the violent crime rate, our preliminary results provide only hints of support for the deterrence hypotheses.

2 Literature Review

This brief literature review includes only a few representative papers (with emphasis on those not included in Moody and Marvell (2008)) from the rich volume of literature on the heated debate over shall-issue laws. For a more complete review on shall-issue laws before 2008, we have found Moody and Marvell (2008) quite useful.

In Lott and Mustard (1997), "Crime, Deterrence and Right-to-Carry Concealed Handguns", the effects of shall-issue laws on crimes were first thoroughly studied with rigorous statistical models. Under the hypothesis that shall-issue laws deter criminals from committing violent crimes by equipping lawful citizens with concealed weapons, Lott and Mustard adopted a fixed-effect panel data model with county level cross-sectional time-series data from 1977 to 1992. With regressions on nine categories of violent and property crimes, they found statistical evidence that support their hypothesis that shall-issue laws reduce violent crimes and increase property crimes (through substitution effects).

Among many papers that followed Lott and Mustard's initial efforts in studying the effects of shall-issue laws, those of Ayres and Donohue (1999, 2003, 2009) stand out as the most comprehensive and influential. In this series of papers that are intended to challenge Lott's hypothesis "more guns, less crime," Ayres and Donohue focused on the following aspects: 1) correcting several important typos in Lott's definition and coding (e.g. adoption years of shall-issue laws in various states), 2) calculating robust standard errors 3) conducting more robustness checks with different control variables (e.g. incarceration rates instead of arrest rates), 4) arguing for the use of state level data instead of county level data be cause of its higher quality, 5) expanding the length of the data set, and 6) generalizing Lott's specification to impose less structure on the model (which Ayres and Donohue call "hybrid model").

In this paper, we take into account all the contributions both Lott and Mustard, and Ayres and Donohue have made to the literature. By introducing the Cohort Panel Data Model to study this topic, we are contribute to the current literature by 1) accounting for forward looking behaviors in the choice of whether or not to enter and exit a life of violent crime. 2) give the restrictions that reduce the CPDM to a standard difference-in-difference model and thereby show how models in the previous literature give rise to omitted variable biases and 3) clean up earlier statistical problems by specifying serially correlation state errors and using generalized least squares and White standard errors and 4) updating the data to the most recent that is currently available.

3 A Cohort Panel Data Model Specification

Here we present a bare bones dynamic model that captures the essence of forward looking behavior for individuals choosing to be violent criminals or not. For simplicity assume that all violent crimes are committed by men and that a life of violent crime is a career choice made between ages 13 and 24 (the entry window). Having chosen this career, thereafter violent criminals commit crimes at a constant rate[1] until they either exit to other careers or retire after age

[1] In the empirical work we allow for this to change with age.

65.[2] To save words, call males 13-24 *youths* and males 13-65 constitute the *population*.

Crucial to a youth's entry decision is the (expected present discounted) value of a life of violent crime. Crucial to the exit decision is the continuation value of a life of violent crime. Assume that without shall issue laws (SIL), these values are such that in each year of his entry window a youth enters a career in violent crime with probability a and that, conditional on having entered, in each year he exits with probability α.

SIL impacts behaviors by changing both the value of a career in violent crime and also the continuation value of that career once such a career has been chosen. Thus, for a given male, the impact of SIL on his behavior in t depends both on whether SIL passed before, during, or after his entry window and whether his age in t is in his entry window or beyond. Here we sketch these impacts, initially assuming the deterrence hypothesis holds and later bringing in possible alternative effects of SIL.

Lott and Mustard (19), henceforth L&M, famously hypothesized that SIL deters violent crime by upping the probability that a perpetrator will be threatened with a gun or shot by his intended victim. With forward looking behaviors, we interpret the *deterrence hypothesis* to mean that the passage of SIL reduces the value of entering a career in violent crime for youths and also reduces the continuation value of a career in violent crime for those who have already entered. These reductions result in three effects, (i) a *negative direct effect on entry, (ii)* a *positive surprise effect* on exits and, importantly, (iii) a *negative selection effect* on exits.

Each effect is determined as follows. With forward looking behavior, the reduction in the value of a career in violent crime deters entry, reducing the entry rate of youths to $a + b$, where $b < 0$ is the *direct effect of SIL on a youth's entrance probability.* In addition for one who is already a criminal, the advent of SIL unexpectedly reduces the continuation value of his career in violent crime, thereby increasing the probability he exits to $\alpha + \beta'$, where $\beta' > 0$ is the *average surprise effect of SIL on exits.* Together, these direct and surprise effects may capture something like the mechanisms that L&M had in mind for their deterrence hypothesis.

But note that under forward looking behavior, the reduction in the value of a career in violent crime has an additional effect. Assuming that males are unobservably heterogeneous in their proclivity for violent crime, those who entered despite the presence of SIL have higher proclivities than those who were deterred. As a result, as compared to an unselected cohort, a cohort of violent criminals who were selected into violent crime under SIL is smaller than otherwise. Furthermore, both its marginal and average member have stronger proclivities for violent crime than otherwise. Hence, selection under SIL lowers the exit probability of (a randomly selected) violent criminal to $\alpha + \beta'$ where $\beta' < 0$ is the *selection effect of SIL on the exit rate.*

[2] The retirement date is arbitrary and called 65 here for convenience. In our empirical work we will explore alternative, younger retirement ages.

The average surprise effect noted above can be resolved into so called *floodgate effects* (see IMS 2011). Assuming that males are unobservably heterogeneous in their proclivities for a life of violent crime, the advent of SIL unexpectedly decreases the continuation value for criminals and those criminals least suited to a life of violent crime exit first, leaving those more suited behind; in this group left behind both the marginal and average violent criminal is more suited to violent crime than the original group and therefore (a randomly chosen survivor) has a lower exit probability. In the next period, the process repeats, further lowering the exit probability. As shown in (IMS 2011) under reasonable assumptions, this sequential selection produces a temporal pattern of exits characterized by a sharp increase in the exit rate immediately after the implementation of SIL (when the floodgate opens), followed by slower and slower exit rates that eventually asymptote out to a long-run exit rate that is higher than the pre-SIL rate, but lower that the initial spike.

The next section translates this model into a specification for estimation.

3.1 Specification for Estimation

Controversies on the intended and unintended effects of gun control laws have gone on for decades. Lott and Mustard (19) famously introduced the deterence effect of shall issue laws (SILs) on violent crime, namely that these laws deter violent crimes by increasing the chance that a perpetrator will be threatened or shot by intended victims who may now bear concealed guns. To date the controversy has been waged with difference-in-difference estimates and state or county level panel data on crime rates. Our goal is to learn whether the deterrence hypothesis or alternatives to it hold up once a researcher accounts for forward looking behaviors. To do so we specify a bare bones dynamic model that accounts for forward looking behaviors of potential and contemporaneous violent criminals. Key to the specification is the need to take it, not to ideal panel data on individuals committing crimes, but to the available data, state and county level panel data on crime rates. As the reader may anticipate, We use a generalization of the cohort panel data model (CPDM) proposed by Iyvarakul, McElroy and Staub (2011), enabling us to separately identify not just a direct effect on entry into crime but also surprise and selection effects of SIL on the contemporaneous criminal population.

Underpinning these effects is that some contemporaneous criminals got into crime before the advent of SIL and others afterward. For those who entered a life of violent crime before SIL, under the deterrence hypothesis, the unanticipated (at the time of entry) advent of SIL lowers the value of continuing a life of violent crime and causes more exits than otherwise. In contrast, those who selected into a life of violent crime after and hence despite the presence of SIL have higher proclivities for a life of violent crime than their contemporaries who were deterred; hence this selected group has a lower rate of exit than otherwise. It follows that after SIL, the rate of exit depends on the mix of those surprised and those selected. Those who were surprised dominate the early years after the adoption of SIL and those who were selected dominate later, and completely taking over once the surprised cohorts have retired.

As a practical matter we do not observe entry and exit rates from careers in violent crime.Hence we first build separate entry and exit equations and then, for each period, difference them to get net entry rate equation. To take this equation to data we transform it into a change in the number of violent crimes. Initially we do this under the assumption that every violent criminal produces a constant number of violent crimes per year[3].

A direct implication of the theory is that in any period the overall entry and exit rates depend, not on just whether SILs are in effect, but on the mix of males in the population: youths in their entry windows, males who entered careers in violent crime prior to SIL and males who entered careers in violent crime under SIL. As applied here, the key idea of the CPDM is to construct the rate for any period as weighted averages of the rates that pertain to each subpopulation. The weights capture the fraction of each subpopulation at t.

To distinguish the necessary subpopulations we define three generations of males and five eras of time. In state s let τ^s be the period (calendar year) that SIL came into effect. Define the Transition Generation as all of the age cohorts that were in their entry window in τ^s. Then the Pre-SIL Generation consists of all age cohorts whose entry windows had already closed by τ^s and the Post-SIL Generation consist of all age cohorts whose entry windows had not opened as of τ^s. In t the cohorts in the population of interest must not yet be retired (over 65). Hence, for the Transition Generation $13 \leq a^{\tau_s} < 25$, for the Pre-SIL Generation $25 \leq a^{\tau_s} \leq 65$ and for the Post-SIL Generation $a^{\tau_s} < 13$. Looking ahead, the rows in Table 1 contain the exit rates for each generation as it passes through the eras when it is active.

We partition time t into eras, the first. The first and last eras are the Old and the New Equilibrium, respectively. These are the years before SIL ($t < \tau_s$) and the years long after SIL ($t - \tau_s \geq 53$).[4] In between are three transition eras, called the Early, Middle and Late Transition Eras. The Early Transition Era ends once the youngest age cohort in the Transition Generation (those 13 in τ_s) ages out of their entry window so that $0 \leq t - \tau_s < 12$. The 12 years in the Middle Transition Era[5] ends once the youngest age cohort in the Pre-SIL Generation (those 25 in τ_s) retires; therefore $12 \leq t - \tau_s < 42$. Thirdly, the 12 years in the Late Transition Era ends once the youngest age cohort in the Transition Generation (those 13 in τ_s) retires; therefore $42 \leq t - \tau_s < 53$.

3.1.1 Contribution of Entries to the Net Entry Rate

[3]We relax this assumption in our empirical work. We maintain, however, the implicit assumption that the number of crimes/year of a criminal is independent of his proclivity for violent crime.

[4]The 53^{rd} years after SIL is the first year by which everyone in the Pre-SIL and Transition Generations is retired. So in the New Equilibrium there are no surprise effects and all violent criminals selected into this career under SIL. Obviously, if the retirement age was assumed to be Δ years earlier, this bound would be lowered to $(53 - \Delta)$ years.

[5]Given retirement after 65, the Middle Transition Era is 29 years long. If the retirement age was assumed to be Δ years earlier, this would be shortened to $(29 - \Delta)$ years long.

This section derives the contribution of the entry rates to the net (entry minus exit) entry rate for the whole population. This contribution is weighted by the fraction of the population in it's entry window.

Table 1 lists the generations in the rows and eras in the columns. It contains the definitions of the generations and of the eras and defines dummy variables for each era. By definition, $I_t^{OldE}+, I_t^{EarlyT}+I_t^{MidT+LateT+NewE}=1$. For each generation in each era, the corresponding cell contains the entry rate given by our model. In parentheses below each entry rate is a weight Y_t^{Gen} defined as the fraction of the population in their entry windows (aged 13-24) at t in generation Gen for $Gen = Pre$, $Trans$, or $Post$. Also, define $Y_t = Y_t^{Pre}+Y_t^{Trans}+Y_t^{Post}$, the the fraction of the population in their entry windows (aged 13-24) at t. Note that we were able to collapse the last three eras into one column since, for each generation the model dictates that these three eras (the Middle and Late Transition Eras and the New Equilibrium) share a common entry rate.[6]

As the first column shows, during Old Equilibrium the entry rate is zero for the Post-SIL Generation (they were not yet old enough to enter) while the entry rate for both the Transition and Pre-SIL Generations is a. Thus during the Old Equilibrium, the contribution of the entry rates to the net entry rate (entry minus exit) is simply the weighted sum or $(Y_t^{Pre}+Y_t^{Trans})a = Y_t a$.

During the Early Transition Era (the middle column) things are more complicated. During this Era cohorts in the Transition Generation are aging out of their entry windows (oldest one first) and thus spend different fractions of their entry windows under SIL. For those cohorts not yet aged out of their entry windows, we require a measure of the average strength of the influence of SIL on their entry decisions. Take a t in the Early Transition Era when those in the Transition Generation still in their entry windows will have completed only part of their entry window and this, in turn, can be divided into $(a^{\tau_s}-13)$ Pre-SIL years and $(t-\tau^s+1)$ years under SIL. Adding gives $(t-\tau^s+a^{\tau_s}-12)$ for the total elapsed years (including t) of their entry windows. Thus, for a cohort that was age a^{τ^s} in τ_s, the fraction of their entry windows to date spent under SIL is $\frac{t-\tau^s+1}{t-\tau^s+a^{\tau_s}-12}$. For t in the Early Transition Era define the weight $W_t^b = \sum\limits_{a^{\tau_s}\in Y_t^{Trans}} \frac{t-\tau^s+1}{t-\tau^s+a^{\tau_s}-12}$, where the sum is over the age cohorts in the Transition Generation that are still in their entry window as of t. This weight measures the average fraction of the incomplete entry windows under SIL exposure of this group to SIL as of t

Using this we can write the averaged entry rate for the Transition Generation in the Early Transition Era as $a + W_t^b b$ and Table 1 records this. The other entry rate in the Early Transition Era applies to the vanguard of the Post-SIL Generation, $(a + b)$. As shown in column two, during the Early Transition Era

[6] Note that the upper left cell as well as three more cells in the lower right hand corner contain zero entry rates and zero weights, $Y_t^{Gen}=0$. In each case the relevant generation had no one in their entry window. For the upper left cell we have that during the Pre-SIL Era the Post-SIL Generation was too young . For the three cells with zeros in the bottom right triangle, all members of the relevant generations were beyond their entry windows during the specified eras.

Cells contain entry rates of youths by generation and era.	Pre-SIL Era	Post-SIL Eras	
	Old Equilibrium $I_t^{OldE} = 1$ $t - \tau_s < 0$	Early Transition $I_t^{EarlyT} = 1$ $0 \leq t - \tau_s < 12$	Middle, Late Transition & New Equilibrium $I_t^{MidT+LateT+NewE} = 1$ $12 \leq t - \tau_s$
Post-SIL Generation: Age cohorts $a_i^{\tau_s} < 13$	0 $(Y_t^{Post} = 0)$	$a + b$ $(Y_t^{Post} > 0)$	$a + b$ $(Y_t^{Post} > 0)$
Transition Generation: Age cohorts $13 \leq a_i^{\tau_s} < 25$	a $(Y_t^{Trans} > 0)$	$a + W_t^b b$ $(Y_t^{Trans} > 0)$	0 $(Y_t^{Trans} = 0)$
Pre-SIL Generation: Age cohorts $25 \leq a_i^{\tau_s} \leq 65$	a $(Y_t^{Pre} > 0)$	0 $(Y_t^{Pre} = 0)$	0 $(Y_t^{Pre} = 0)$
Population weighted column sum	$(Y_t^{Pre} + Y_t^{Trans})a$	$(Y_t^{Trans} + Y_t^{Post})a + \left(W_t^b Y_t^{Trans} + Y_t^{Post}\right) b$	$Y_t^{Post} a + Y_t^{Post} b$

Table 1: Entry Rates by Generations (rows) and Eras (columns). The Y's in parentheses give population weights for youths (those ages 13-24) in each generation when t is in the relevant era (column).

the weighted sum, $Y_t a + (Y_t^{Post} + W_t^b Y_t^{Trans})b$ is the contribution of entry to the net entry rate (entry minus exit) we seek.

Moving to the last column which encompasses three eras, note that the earliest one begins as soon as the entry window for the Transition Generation closes. By definition, in this era the Transition Generation is too old to enter and the still older Pre-SIL Generation is perforce also too old. Hence the corresponding weights are $Y_t^{Trans} = Y_t^{Pre} = 0$. Only the Post-SIL generation has a positive weight ($Y_t^{Post} > 0$); its entry rate is $a + b$, reflecting the full force of the direct effect of SIL on entry. Thus, during each of the last three eras, as recorded as the weighted column sum for the third column, the contribution of entry rates to the net entry rate (entry minus exit) is $Y_t^{post}(a + b) = Y_t(a + b)$.

We turn now to the contribution of exit to the net entry rate.

3.1.2 Contribution of Exits to the Net Entry Rate

Table 2 has a format similar to Table 1 but here we need five columns to distinguish all five eras. Each cell contains the exit rate implied by our model for the corresponding generation and era In parentheses below each rate is a weight, A_t^{Gen} defined as the fraction of the population 25 though 65 in t where $Gen = Pre$, $Trans$, or $Post$. In any t, $A_t^{Pre} + A_t^{Trans} + A_t^{Post} = A_t$, the fraction of the population aged 25 though 65 in t. As in Table 1, some generations are too young or two old to be exiting during some some eras. Thus there are two zeros in the upper left when the Post-SIL Generation was too young for exits and three zeros in the lower right corresponding to eras when the Transition or the Pre-SIL or both generations had retired.

The exit rates in the table come directly from our model. The (nonzero) rates of exit from crime for the Post-SIL Generation (first row) in the last three eras are all $\alpha + \beta$, reflecting the fact every violent criminal in this generation selected into a career of violent crime despite the presence of SILs and were thus more suited to the profession and less likely to exit ($\beta < 0$). In the Old Equilibrium (column 1) exit rates of criminals in both the Transition and Pre-SIL Generations (second and third rows) were unaffected by SIL ($\alpha > 0$). But, after SIL and before retirement (i.e., during the Early and Middle Transition Eras (columns 2 and 3)), the rates of exit for the Pre-SIL generation are $\alpha + \beta'$, reflecting the fact that every one who had already chosen to be a violent criminal prior to the advent of SIL suffered a surprise reduction in their continuation value of crime and therefore were more likely to exit and so their exit rate is $(\alpha + \beta')$ with $\beta' > 0$.

The exit rates for the Transition Generation (second row) in the Transition Eras are given as $\left(\alpha + W_t^{\beta'}\beta' + W_t^{\beta}\beta\right)$, with some weight on both the surprise and selection effects. This reflects the fact that in this generation during these eras all violent criminals either selected into violent crime despite SILs or entered before SILs and were surprised by their advent.

Cells contain exit rates of adults by generation and era.	Pre-SIL Era	Post-SIL Eras			
	Old Equilibrium (No selection at entry; none surprised in t.) $I_t^{OldE}=1$ $t-\tau_s<0$	Early Transition (Some adults selected at entry; some surprised in t.) $I_t^{EarlyT}=1$ $0\leq t-\tau_s<12$	Mid Transition (Some adults selected at entry; some surprised in t.) $I_t^{MidT}=1$ $12\leq t-\tau_s<42$	Late Transition (Some adults selected at entry; some surprised in t.) $I_t^{LateT}=1$ $42\leq t-\tau_s<53$	New Equilibrium (All adults selected at entry; none surprised in t.) $I_t^{NewE}=1$ $53\leq t-\tau_s$
Post-SIL Generat = Age cohorts $a_i^{\tau_s}<13$	0 $(A_t^{Post}=0)$[7]	0 $(A_t^{Post}=0)$[8]	$\alpha+\beta$ $(A_t^{Post}>0)$	$\alpha+\beta$ $(A_t^{Post}>0)$	$\alpha+\beta$ $(A_t^{Post}>0)$
Transition Generat = Age cohorts $13\leq a_i^{\tau_s}<25$	α $(A_t^{Trans}>0)$	$\left(\alpha+W_t^{\beta}\beta'+W_t^{\beta}\beta\right)$ $(A_t^{Trans}>0)$	$\left(\alpha+W_t^{\beta}\beta'+W_t^{\beta}\beta\right)$ $(A_t^{Trans}>0)$	$\left(\alpha+W_t^{\beta}\beta'+W_t^{\beta}\beta\right)$ $(A_t^{Trans}>0)$	0 $(A_t^{Trans}=0)$[9]
Pre-SIL Generation = Age cohorts $25\leq a_i^{\tau_s}\leq 65$	α $(A_t^{Pre}>0)$	$\alpha+\beta'$ $(A_t^{Pre}>0)$	$\alpha+\beta'$ $(A_t^{Pre}>0)$	0 $(A_t^{Pre}=0)$[10]	0 $(A_t^{Pre}=0)$[11]
Weighted column sum	$A_t\alpha$	$A_t\alpha+$ $+A_t^{Trans}W_t^{\beta}\beta$ $\left(A_t^{Pre}+A_t^{Trans}W_t^{\beta'}\right)\beta'$	$A_t\alpha+$ $+\left(A_t^{Trans}W_t^{\beta}+A_t^{Post}\right)\beta$ $\left(A_t^{Pre}+A_t^{Trans}W_t^{\beta'}\right)\beta'$	$A_t\alpha+$ $\left(A_t^{Trans}W_t^{\beta}+A_t^{Post}\right)\beta$ $A_t^{Trans}W_t^{\beta'}\beta'+$	$A_t\alpha+$ $A_t\beta$

Table 2: Exit Rates by Generations (rows) and Eras (columns). The A's in parentheses give population weights for adults (those ages 25-65) in each generation when t is in the relevant era (column).

In the Old Equilibrium members of the Post-SI Generation were not yet 13 and perforce, not yet adults
In the Early Transition Era members of the Post-SI Generation were not yet adults (not 24-65 years old).
By the New Equilbrium all criminals of the Transition Generation have retired (passed age 65).
By the Late Transition Era all criminals in the Pre-SI Generation have retired.
By the New Equilibrium all criminals in the Pre-SI generation have been retired for at least 13 years.

The Early Transition Era begins with the advent of SIL and in that first year (τ_s)every cohort in the Transition Generation is represented. One year later the oldest cohort ($a^{\tau_s} = 24$) has aged out of its entry window, having spent $\frac{1}{12}^{th}$ of its entry window under SIL. Another year later the next oldest cohort ($a^{\tau_s} = 23$) has aged out of its transition window, having spent $\frac{2}{12}^{th}$ of its entry window under SIL. This process continues until the last and 12^{th} year of this era when youngest cohort of the transition generation ($a^{\tau_s} = 13$) is 24 years old and has spent the whole $\left(\frac{12}{12}\right)^{th}$ of its entry window under SIL. In general, by the time cohort a^{τ_s} has turned 25 it has aged out of its entry window with $\frac{(25-a^{\tau_s})}{12}$ of its entry window spent under SIL and $\frac{(a^{\tau_s}-13)}{12}$of it's entry window was spent prior to SIL. Averaging this fraction over all cohorts in the Transition Generation that are past their entry windows (older than 24) yields and weighting each fraction by the fraction of adults in t in the corresponding cohort ($n\left(a^{\tau_s}, t\right)$) the weight $W_t^{\beta'} = \sum_{a^{\tau_s}=13}^{24} n(a^{\tau_s}, t)\frac{(a^{\tau_s}-13)}{12}$. This, in turn, is applied to the surprise effect, reflecting the extent to which this generation's exits are influenced by the unexpected drop in the continuation value. As members of this generation were either surprised or selected, $W_t^{\beta} = (1 - W_t^{\beta'})$ is the weight on the selection effect, reflecting the extent to which this generation's exits are influenced by selection under SIL at entry.[12].

3.1.3 The Empirical Specification

For any given era at time t, the net entry rate for the population is simply the contribution from entries minus the contribution from the exits. The weights on the entries and exits are the fractions of the population at risk for entry and exit For each era these are recorded, respectively, as the weighted column sums in the bottom rows of Table 1 and Table **??**. We can write the net entry equation by taking these column sums, multiplying each by the corresponding era dummy (I_t^{Era}) and subtracting the resulting exit terms from the entry terms for each era. Then collecting terms on the five unknown parameters and adding an appropriate error term yields the net entry into violent crime as

$$E_{st} = Y_t a + \left[\left(W_t^b Y_t^{Trans}\right) I_t^{EarlyT} + Y_t^{Post} I_t^{ErlyT+MidT+LateT+OldE}\right] b$$
$$-A_t\alpha - \left[W_t^{\beta} A_t^{Trans} I_t^{ErlyT+MidT+LateT} + A_t^{Post} I_t^{MidT+LateT} + A_t I_t^{NewE}\right]\beta$$
$$-\left[A_t^{Pre} I_t^{ErlyT+MidT} + W_t^{\beta'} A_t^{Trans} I_t^{ErlyT+MidT+LateT}\right]\beta' + \epsilon_{st} \ , \tag{1}$$

[12]Note that if at each point in time t, the 12 cohorts are the same size (but from period to period they could all change size together), then $W_t^{\beta'} = W_t^{\beta} = \frac{1}{2}$.

where we hold off on discussing the error properties. If we observed entry and exit rates for violent criminals, (1) would be the appropriate empirical specification. As we do not we transform (1) to the change in violent crimes per year. Under the simplest possible assumption that all violent criminals commit κ crimes per year this yields

$$\Delta C_{st} = Y_t\, \kappa a + \left[\left(W_t^b Y_t^{Trans} \right) I_t^{EarlyT} + Y_t^{Post} I_t^{ErlyT+MidT+LateT+OldE} \right] \kappa b$$

$$-A_t\, \kappa\alpha - \left[W_t^{\beta} A_t^{Trans} I_t^{ErlyT+MidT+LateT} + A_t^{Post} I_t^{MidT+LateT} + A_t I_t^{NewE} \right] \kappa\beta$$

$$- \left[A_t^{Pre} I_t^{ErlyT+MidT} + W_t^{\beta'} A_t^{Trans} I_t^{ErlyT+MidT+LateT} \right] \kappa\beta' + \kappa\epsilon_{st}.,. \tag{2}$$

With regard to the error term we resolve it into state and year fixed effects as well as linear and quadratic state-specific time trends and allow for within-state autocorrelated errors. The identified parameters are then κa and -$\kappa\alpha$, the Pre-SIL increases and decreases in crime due to entry and exit from careers in violent crime, and the Post-SIL deviations from the Pre-SIL changes in crime rates. The latter are κb due to the direct effect of SIL on entry, $-\kappa\beta$ due to the selection effect of SIL on exits and $-\kappa\beta'$ due to the surprise effect on exits.

We need to addresses two potential problems with (2). First, κ =crimes per criminal no doubt varies systematically with age. To address this in some of the empirical work we weight each age-cohort according to a proxy for the fraction of crimes per criminal by age deduced from arrest rates. Second, in (2), the A_t^{Gen}'s are the shares of adult violent criminals in the population and we are aware of no data on this. In our initial empirical work we have used the shares of adults in the population as a crude proxy, In future work we can hone in on the active criminal population by removing the institutionalized, those with full time employment and so forth.

Finally, he average surprise effect can be regarded as a lifetime average effect and can be above can be resolved into so called *floodgate effects* (see IMS 2011). Assuming that males are unobservably heterogeneous in their proclivities for a life of violent crime, the advent of SIL unexpectedly decreases the continuation value for criminals and those criminals least suited to a life of violent crime exit first, leaving those more suited behind; in this group left behind both the marginal and average violent criminal is more suited to violent crime than the original group and therefore (a randomly chosen survivor) has a lower exit probability. In the next period, the process repeats, further lowering the exit probability. As shown in (IMS 2011) under reasonable assumptions, this sequential selection produces a temporal pattern of exits characterized by a sharp increase in the exit rate immediately after the implementation of SIL (when the floodgate opens), followed by slower and slower exit rates that eventually asymptote out to a long-run exit rate that is higher than the pre-SIL rate, but lower that the initial spike.

3.1.4 Interpreting the change in crime rate

First note that we can collapse the CPDM model to a difference in difference model as follows. Impose the restrictions that $\alpha = a$, $\beta' = \beta = b$.and $\kappa = 1$. This erases the differences between entry and exits and makes distinctions among generations irrelevant so that the A and Y weights aggregate to just a single population weight which equals one for all t. These restrictions also collapses the eras into just two, one Pre-SIL and one Post-SIL. Let I_t^{Post} be the indicator for the Post-SIL era. Then under these restrictions and (2) collapses to

$$\Delta C_{st} = a + I_t^{Post} b + \epsilon_{st}. \tag{3}$$

Under the assumed error structure from above (including state and year fixed effects) this a standard difference in difference specification for the growth of the crime rate.

Inspection of (2) reveals how, at a point in time t, the distribution of the population across generations controls the rate of change in crime rates. It also reveals as well how changes in this distribution across and within eras controls the evolution of the rate of change of crime rates over time. For example, in the Early Transition Era the active generations satisfy $Y_t^{Trans} + Y_t^{Post} + A_t^{Pre} + A_t^{Trans} = 1$ and in the Late Transition Era they satisfy $Y_t^{Post} + A_t^{Trans} + A_t^{Post} = 1$. Correspondingly, the exits go from being highly weighted toward the surprises suffered by those who entered prior to SIL (A_t^{Pre}) to being highly weighted toward those who selected into crime after SIL (A_t^{Post}). More generally, one initial effect of the adoption of SIL is surprise effects. But as time passes, the younger generations gradually replace the older reducing the weight of the surprise effect and increasing the weight of the selection effect until finally, in the New Equilibrium, the surprise effect has disappeared altogether.

Note that if the CPDM is the correct model, the estimate of b from the difference-in-difference model will be a weighted average of direct, surprise and selection effects and the weights will depend on the eras spanned by the data. For example if the data cover Pre-SIL and Early Transition Eras, the sample will be dominated by the Pre-SIL generation and the surprise effect will have a large weight at the expense of the selection effect, so that the diff-in-diff estimate of b will tend to be an estimate of the combined direct and surprise effects. Further, as the data set lengthens to cover longer and longer time spans, the weight on the selection effect grows at the expense of the weight on the surprise effect. As these are opposite in sign, the effect of SIL estimated using a difference-in- difference model will automatically diminish with the length of the sample. While these patterns are easily understood in the light of a CPDM model, when viewed only from a diff-in-diff prospective, they tend to fuel needless controversy.

4 Data Description

In the current version of the paper, unless otherwise noticed, we use state level data from 1977 to 2007 (results from a more up-to-date data set will be reported on the next draft of the paper). Our current data set mainly consists of individual birth group population from Surveillance Epidemiology and End Results (SEER) Program operated by the National Cancer Institute, crime data from the Uniform Crime Report (UCR) maintained by the Federal Bureau of Investigation (FBI), and income and other control variables obtained from previous literature. In Table 1, we provide some summary statistics on most of the variables we are using in our regressions.

4.1 Mean VC Rates of SIL-Adopting Waves

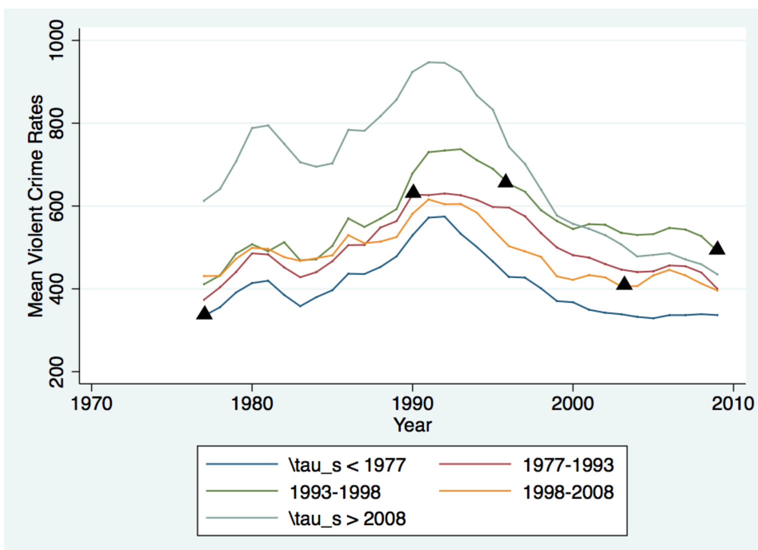

Figure 1: Mean VC Rates of SIL-Adopting Waves

In Figure 1, we divide the 51 states into 5 groups by how early they adopt shall-issue laws: before 1977 (beginning of the sample), between 1977 and 1992, between 1993 and 1997, between 1998 and 2007, after 2008 (end of the sample). Ayres and Donohue (2003) has a similar graph with slightly different group cutoffs and only extend to 1999. We picked our group cutoff years according to the three biggest waves of SI adoptions in Figure 2 to be more intuitive and consistent.

Within each group, we calculate the population-weighted mean violent crime rates in each year and plot them accordingly (see Appendix 1). On each line, we mark with a solid triangle to indicate the median year of SI adoption within that group. We see clearly that 1) all groups' violent crime rates peak at the early 1990's regardless of their median SI adoption year, 2) the relative positions of the violent crime rates change at the end compared to the beginning of the sample (the 4 top lines have several intersections during the sample period).

4.2 Miscellaneous

Since previous literature all have minor discrepancies in the adoption years of shall-issue laws in several states, we have conducted independent research on these adoption dates. Our result only differs from Ayres and Donohue's in two states (North Dakota and South Dakota), each only by one year. All of the results presented in this draft are based on our adoption years. Robustness checks with Ayres and Donohue's adoption years are done but not reported.

Throughout this paper, we have assumed uniform distribution of violent crimes among birth groups of qualified males. One immediate problem with this assumption is the sudden drop in violent crimes past a certain age. We have adopted two ways to deal with this problem. First, we adopt a "retirement age" of violent criminals at 45, 55, or 65, after which we assume there would be no violent criminals. Results using this method is reported in Tables 2-5. Second, we have obtained data on arrest rates among (almost single-aged) birth groups from the UCR. We will use this as a proxy for how many crimes are actually conducted in each birth group and weight different birth groups by their respective arrest rates. Results will also be reported in the next draft.

A few other incidents in the data are worth mentioning. The Oklahoma City bombing which results in 168 casualties in 1995 (which was, coincidentally, also the adoption year of shall-issue law in Oklahoma state), was originally included in the UCR data in the murder category, resulting in a huge increase in murder that year. We have thus taken it out and showed that it doesn't affect our results. Murder resulted from events of September 11, 2001 in New York, on the other hand, were not included in the data, and we will leave it that way. We have also accounted for the fact that Philadelphia adopted shall-issue laws later than the State of Pennsylvania did. Lastly, there are several years where various states were unable to report their crime data to the FBI and thus the corresponding data are estimated from interpolation. We have thus tried flagging these data points and only estimated our model on the reported data. We see no significantly different result from this exercise.

5 Empirical Results

In Tables 2 to 5, we present some preliminary results from our model with comparison to the plain difference-in-differences model similar to Lott's spline model (except that we don't force any structure on the before and after trend) and Ayres and Donohue's hybrid model. In these four tables, the first column presents regression results from our full model with all standard control variables as used in the previous literature (Coefficients are: base entry rate, direct effects of SIL, base exit rates, selection effects, and surprise effects, respectively). Second column presents an immediate comparison with the plain differences-in-differences model with all control variables. If CPDM is correctly specified, the coefficient of shall-issue dummy should be a weighted average of the estimated direct, surprise, and selection effects. In the third column, to justify the use of these control variables, we exclude all the demographic and income variables and only kept state and time fixed effects and linear and quadratic state-specific time trends. Similarly, we pair it with the plain differences-in-differences model results for comparison. In columns 5-12, we present results obtained from specific types of violent crimes defined by the FBI and as done in previous literature. All reported estimates and standard errors are obtained from generalized least squares and accounted for serial correlation as discussed by Bertrand et al. (2004).

We have found our results consistent with our theory and the deterrence hypothesis (note the same signs with our corresponding theoretical layout). In particular, among all the violent crime categories, murder and rape come out to be the most statistically significant and consistent with our theory. As we have seen from previous literature as well as from the comparison of the 4 tables here, the length of the sample period matters a lot. In Lott and Mustard (1997) and our Table 4 and 5, the sample ends at 1992, which is, coincidentally, the end of the first big wave of adoption of shall-issue laws among states, as shown in Figure 2.

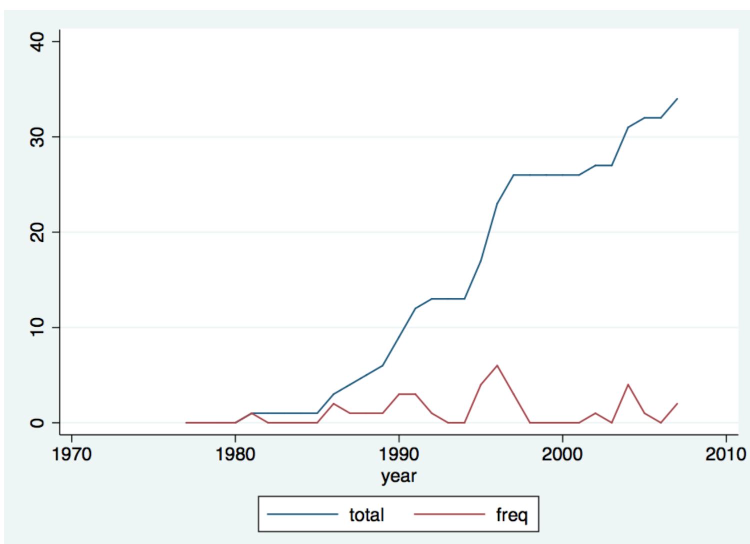

Figure 2: Trend of Adoption of Shall-Issue Laws

Since in both Lott and Ayres and Donohue's differences-in-differences model, the estimates of the coefficients on the effects of shall issue law are weighted average of direct, surprise, and selection effects, the length of coverage of different cohorts would thus lead to different directions of the effect due to the conflicting forces between the three effects. Accidentally ending the sample after a wave of adoption of shall-issue laws, i.e. covering only Pre-SIL and Early Transition Eras, will show dominant effects of surprise and minimal selection effects, which at least partially explains Lott's results. On the other hand, Ayres and Donohue's model, when estimated at a much later point in time, captures much of the Post-SIL generation and thus puts more weight on the selection effect than surprise effects and thus shows the opposite direction of the effects. As shown in Figure 3, the immediate effects of shall-issue laws are dominated by the surprise effects of older cohorts, which increases the exit rate and decreases the overall violent crime rates. However, as time goes by, the selection effects from the younger cohorts start to kick in to bring the violent crimes back up. Therefore, depending on where the researcher's sample ends, one could reach very misleading conclusion even with rigorous statistical models.

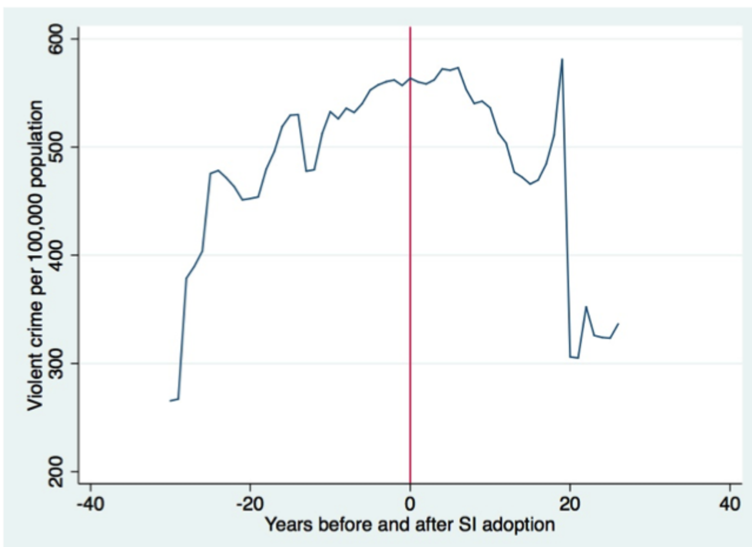

Figure 3: Violent Crimes Before and After the Adoption of Shall-Issue Laws

In our regressions, we have divided the post-adoption time into 5 periods: 1-2 years, 3-5 years, 6-10 years, 11-20 years, and 21 and more years. We constructed five dummies to represent each period and investigated how the surprise effects evolve over time. We can clearly see that the magnitude of surprise effects vanishes over time. In Table 6, we also tested the joint significance of the surprise effects to confirm our theory of the conflicting forces between surprise effects and selection effects during different time periods. Again, for murder and rape, we see clearly that surprise effects are more dominant if we end our sample in 1992 and the significance of surprise effects largely depends on the length of our data set.

In the next draft of the paper, we will report results of: 1) up-to-date data set and 2) weighted crime rates in each birth group by their respective arrest rates.

Table 1: **Summary statistics**

Variable	Mean	Std. Dev.	Min.	Max.	N
State Population	5045867.716	5575525.208	403000	36553215	1581
Crime Rates					
Violent	485.306	313.105	47	2921.8	1581
Murder	7.08	7.08	0.2	80.600	1581
Rape	34.9	13.855	7.3	102.2	1581
Robbery	150.519	156.056	6.4	1635.1	1581
Aggravated Assault	292.806	172.815	31.3	1557.6	1581
Log Crime Rates					
Violent	6.005	0.619	3.85	7.98	1581
Murder	1.696	0.709	1.853	4.39	1581
Rape	3.476	0.396	1.988	4.627	1581
Robbery	4.632	0.931	1.856	7.399	1581
Aggravated Assault	5.504	0.623	3.444	7.351	1581
Change of Crime Rates					
Violent	6.697	49.182	-510.964	349.321	1530
Murder	-0.006	1.464	-18.147	23.226	1530
Rape	0.66	4.261	-20.566	41.505	1530
Robbery	0.821	27.104	-367.297	311.224	1530
Aggravated Assault	5.222	31.37	-178.7	316.129	1530
Cohorts					
Old Mature	0.214	0.068	0	0.3	1581
Middle Mature	0.017	0.029	0	0.097	1581
Young Mature	0.019	0.058	0	0.27	1581
Explanatory Variables					
Entry	0.096	0.012	0.074	0.134	1581
Shall Entry	0.034	0.045	0	0.121	1581
Exit	0.25	0.017	0.203	0.3	1581
Selection	0.028	0.061	0	0.270	1581
Surp1-2	0.01	0.05	0	0.294	1581
Surp3-5	0.014	0.055	0	0.285	1581
Surp6-10	0.019	0.063	0	0.259	1581
Surp11-20	0.02	0.061	0	0.245	1581
Surp21-	0.005	0.022	0	0.184	1581
Control Variables					
Violent Arrest Rate	37.652	18.943	0.578	558.810	1481
Density	356.441	1344.887	0.697	11176.492	1581
Income	18839.326	12166.232	2114.199	72239.094	1581
Welfare	251.056	188.247	12.931	1154.863	1581
Unemployment	76.623	58.486	5.622	415.203	1581

Table 2: CPDM with (Logarithm of) Level of Violent Crime Rate as Dependent Variable with Retirement Age at 45

(1977-2007) 50 states, DC	Violent	DD	Violent w/o X's	DD	Murder	DD	Rape	DD	Aggravated Assault	DD	Robbery	DD
Constant		6.563***		5.956***		0.528		4.927***		6.228***		5.389***
		(0.499)		(0.117)		(0.691)		(0.434)		(0.599)		(0.770)
Shall		-0.005		-0.006		0.033		-0.008		-0.005		0.008
		(0.009)		(0.010)		(0.017)		(0.011)		(0.012)		(0.015)
Entry	5.786***		7.815***		9.785***		11.29***		4.195*		13.65***	
	(1.379)		(1.353)		(2.012)		(1.457)		(1.656)		(2.158)	
Shall Entry	1.511*		1.423*		-1.380		-0.849		2.555**		0.795	
	(0.697)		(0.703)		(1.132)		(0.773)		(0.891)		(0.989)	
Exit	-0.258		1.098		8.233***		6.069***		-0.703		3.684	
	(1.538)		(1.480)		(2.371)		(1.706)		(1.851)		(2.286)	
Selection	1.765***		1.694***		2.494***		1.934***		1.702*		0.801	
	(0.502)		(0.495)		(0.662)		(0.450)		(0.677)		(0.693)	
Surp1-2	-0.846*		-0.816*		0.990		0.431		-1.423**		-0.410	
	(0.392)		(0.396)		(0.631)		(0.432)		(0.499)		(0.559)	
Surp3-5	-0.820*		-0.791*		0.866		0.296		-1.331**		-0.518	
	(0.390)		(0.394)		(0.626)		(0.430)		(0.499)		(0.554)	
Surp6-10	-0.782*		-0.751		0.789		0.329		-1.239*		-0.614	
	(0.395)		(0.400)		(0.635)		(0.435)		(0.505)		(0.559)	
Surp11-20	-0.773		-0.725		0.783		0.335		-1.322*		-0.413	
	(0.415)		(0.420)		(0.679)		(0.459)		(0.528)		(0.584)	
Surp21-	0.155		-0.00118		2.901*		-0.494		-0.910		2.335*	
	(0.712)		(0.703)		(1.273)		(0.753)		(0.921)		(0.990)	
Observations	1525	1525	1530	1530	1525	1525	1525	1525	1525	1525	1525	1525
χ^2	3e7	2e5	3e7	2e5	2e6	2e5	1e7	1e5	2e7	1e5	7e6	2e5

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Control variables (arrest rate, population density, income, unemployment, welfare, state and year fixed effects and time trends) are not reported.

Table 3: CPDM with Change of Violent Crime Rate as Dependent Variable with Retirement Age at 45

(1977-2007) 50 states, DC	Violent	DD	Violent w/o X's	DD	Murder	DD	Rape	DD	Aggravated Assault	DD	Robbery	DD
Constant		144.3		6.336		4.633		16.29		90.30		-66.59
		(168.9)		(30.15)		(3.965)		(10.13)		(107.6)		(87.26)
Shall		1.142		-0.396		-0.170*		0.0633		-1.451		0.856
		(3.435)		(3.397)		(0.0805)		(0.264)		(2.301)		(1.488)
Entry	977.4**		935.9**		20.76*		27.17		498.7*		233.2	
	(352.1)		(347.3)		(8.062)		(25.26)		(242.8)		(164.6)	
Shall Entry	33.94		0.406		-4.491		-19.56		47.48		23.41	
	(195.7)		(193.3)		(4.452)		(14.92)		(139.0)		(89.41)	
Exit	-90.38		-560.1		8.371		-51.02		-119.9		-71.81	
	(438.3)		(428.2)		(10.06)		(31.44)		(304.0)		(201.9)	
Selection	53.01		45.06		1.400		14.82		36.55		-38.78	
	(119.6)		(107.6)		(2.592)		(9.501)		(76.52)		(53.98)	
Surp1-2	-20.69		-7.236		1.661		11.45		-43.08		-3.360	
	(111.3)		(109.3)		(2.473)		(8.301)		(77.80)		(51.44)	
Surp3-5	-14.97		3.204		1.361		9.022		-35.27		-17.46	
	(108.6)		(106.3)		(2.425)		(8.071)		(75.71)		(50.34)	
Surp6-10	45.81		65.28		2.409		15.40		2.145		-6.488	
	(109.3)		(107.0)		(2.428)		(8.013)		(75.81)		(50.30)	
Surp11-20	25.53		38.78		4.117		12.73		-42.33		8.678	
	(119.8)		(117.6)		(2.758)		(8.758)		(84.26)		(53.78)	
Surp21-	-68.53		-153.0		6.971		-9.542		-227.7		-7.784	
	(225.7)		(209.6)		(5.673)		(17.59)		(154.6)		(99.67)	
Observations	1525	1525	1530	1530	1525	1525	1525	1525	1525	1525	1525	1525
χ^2	957.2	894.2	1001.1	936.2	391.9	381.7	929.2	757.6	827.2	753.0	563.4	586.8

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Control variables (arrest rate, population density, income, unemployment, welfare, state and year fixed effects and time trends) are not reported.

Table 4: CPDM with (Logarithm of) Level of Violent Crime Rate as Dependent Variable with Retirement Age at 45

(1977-1992) 50 states, DC	Violent	DD	Violent w/o X's	DD	Murder	DD	Rape	DD	Aggravated Assault	DD	Robbery	DD
Constant		4.961		5.493***		-4.655		8.921**		-0.0869		9.388*
		(2.633)		(0.0653)		(4.280)		(3.282)		(2.569)		(4.014)
Shall		0.008		0.010		-0.033		-0.010		0.005		0.004
		(0.016)		(0.016)		(0.030)		(0.015)		(0.016)		(0.023)
Entry	3.880		5.575**		-6.653*		8.927***		2.708		1.790	
	(2.080)		(1.884)		(2.998)		(2.595)		(2.409)		(2.388)	
Shall Entry	0.886		0.194		-1.838		-1.282		1.362		-0.444	
	(1.404)		(1.353)		(2.527)		(1.658)		(1.541)		(1.736)	
Exit	-2.597		4.639*		5.114		0.435		-3.099		3.050	
	(2.693)		(2.327)		(4.735)		(3.536)		(2.844)		(3.828)	
Selection	7.527***		8.328***		2.717		1.499		11.48***		0.489	
	(1.900)		(2.037)		(3.343)		(1.791)		(2.599)		(2.633)	
Surp1-2	-0.463		-0.0525		0.899		0.596		-0.636		0.276	
	(0.805)		(0.772)		(1.457)		(0.937)		(0.891)		(1.020)	
Surp3-5	-0.375		0.0488		0.593		0.461		-0.459		0.188	
	(0.792)		(0.757)		(1.433)		(0.916)		(0.878)		(1.008)	
Surp6-10	-0.659		-0.191		-1.059		1.213		-0.811		-0.169	
	(0.811)		(0.776)		(1.413)		(0.944)		(0.907)		(1.015)	
Surp11-20	-0.0571		0.0765		-0.139		1.008		-0.887		0.838	
	(0.887)		(0.857)		(1.505)		(1.006)		(1.000)		(1.101)	
Surp21-	-0.399		-0.776		-1.431		1.340		-1.341		2.461	
	(1.330)		(1.310)		(2.269)		(1.353)		(1.536)		(1.769)	
Observations	816	816	816	816	816	816	816	816	816	816	816	816
χ^2	2e7	3e5	6e7	4e5	4e6	2e5	2e7	2e5	1e7	3e5	2e7	6e5

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Control variables (arrest rate, population density, income, unemployment, welfare, state and year fixed effects and time trends) are not reported.

Table 5: CPDM with Change of Violent Crime Rate as Dependent Variable with Retirement Age at 45

(1977-1992) 50 states, DC	Violent	DD	Violent w/o X's	DD	Murder	DD	Rape	DD	Aggravated Assault	DD	Robbery	DD
Constant		-756.3		49.52*		2.430		110.1		1371.2		1205.2
		(2430.7)		(20.42)		(78.07)		(116.3)		(804.7)		(1634.9)
Shall		-4.753		-4.115		-0.372*		-0.149		-2.534		-1.109
		(5.421)		(5.424)		(0.149)		(0.393)		(3.556)		(2.910)
Entry	854.5		1428.2*		-14.16		191.1***		1015.2*		-260.2	
	(653.2)		(567.3)		(20.33)		(54.86)		(409.4)		(398.6)	
Shall Entry	54.11		-7.796		1.968		-95.21**		163.5		2.362	
	(470.2)		(463.7)		(14.67)		(35.13)		(304.0)		(267.6)	
Exit	-2812.7*		-604.7		-33.19		-182.3		-221.7		-2296.8***	
	(1204.4)		(1034.7)		(33.02)		(96.23)		(706.2)		(651.6)	
Selection	882.9		738.2		29.10*		89.43*		322.8		446.3	
	(556.6)		(554.1)		(13.03)		(44.46)		(331.9)		(297.3)	
Surp1-2	-61.19		-11.96		-2.757		53.48**		-116.0		-3.994	
	(277.3)		(271.6)		(8.471)		(20.11)		(180.4)		(159.9)	
Surp3-5	-95.51		-70.22		-5.000		47.13*		-114.2		-38.36	
	(269.6)		(264.0)		(8.164)		(19.49)		(174.7)		(155.8)	
Surp6-10	-131.6		-110.6		-7.842		61.17**		-143.3		-69.53	
	(269.4)		(264.2)		(8.168)		(18.87)		(175.6)		(158.9)	
Surp11-20	-329.7		-353.9		-4.201		45.11*		-306.5		-86.65	
	(296.7)		(289.1)		(8.728)		(19.86)		(188.4)		(172.6)	
Surp21-	-628.0		-830.8		7.468		-7.372		-796.5**		65.67	
	(474.7)		(457.2)		(12.14)		(31.81)		(278.8)		(265.6)	
Observations	816	816	816	816	816	816	816	816	816	816	816	816
χ^2	1200.9	806.5	1163.6	768.1	445.5	436.8	1333.9	653.9	1292.7	795.1	483.9	467.7

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Control variables (arrest rate, population density, income, unemployment, welfare, state and year fixed effects and time trends) are not reported.

Table 6: Joint Significance of Surprise Effects

	Violent	Violent w/o X's	Murder	Rape	Aggravated Assault	Robbery
77-07 (level)	0.888	0.885	0.052	0.524	0.263	0.011*
77-92 (level)	0.578	0.761	0.003**	0.252	0.398	0.035*
77-07 (change)	0.102	0.143	0.293	0.006**	0.044*	0.658
77-92 (change)	0.660	0.252	0.030*	0.000***	0.013*	0.584

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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6 Appendix

6.1 population-weighted within-wave mean violent crime rates

At a certain point in time, let V_i be the number of violent crimes in state i in that year, P_i be the population in the same state in that year. Then let v_i be the violent crime rates in state i defined as the number of violent crimes per 100,000 population:

$$v_i = \frac{V_i}{P_i} * 100000 \tag{1}$$

Let W_j be the total population of all states in the same wave j ($j = 1, 2, 3, 4, 5$):

$$W_j = \sum_{i \in j} P_i \tag{2}$$

And define the weights as the population percentage within the same wave:

$$w_i = \frac{P_i}{W_j}, \forall i \in j \tag{3}$$

Finally, the population-weighted within-wave mean violent crime rate of wave j is $\overline{v}_j$:

$$\overline{v}_j = \frac{1}{\sum_{i \in j} 1} v_i w_i = \frac{1}{\sum_{i \in j} 1} \frac{V_i}{W_j} * 100000 \tag{4}$$