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

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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 $W_t^b = \sum_{a^{\tau_s} \in Y_t^{Trans}} \frac{t-\tau^s+1}{t-\tau^s+a^{\tau_s}-12}$, 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

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

[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

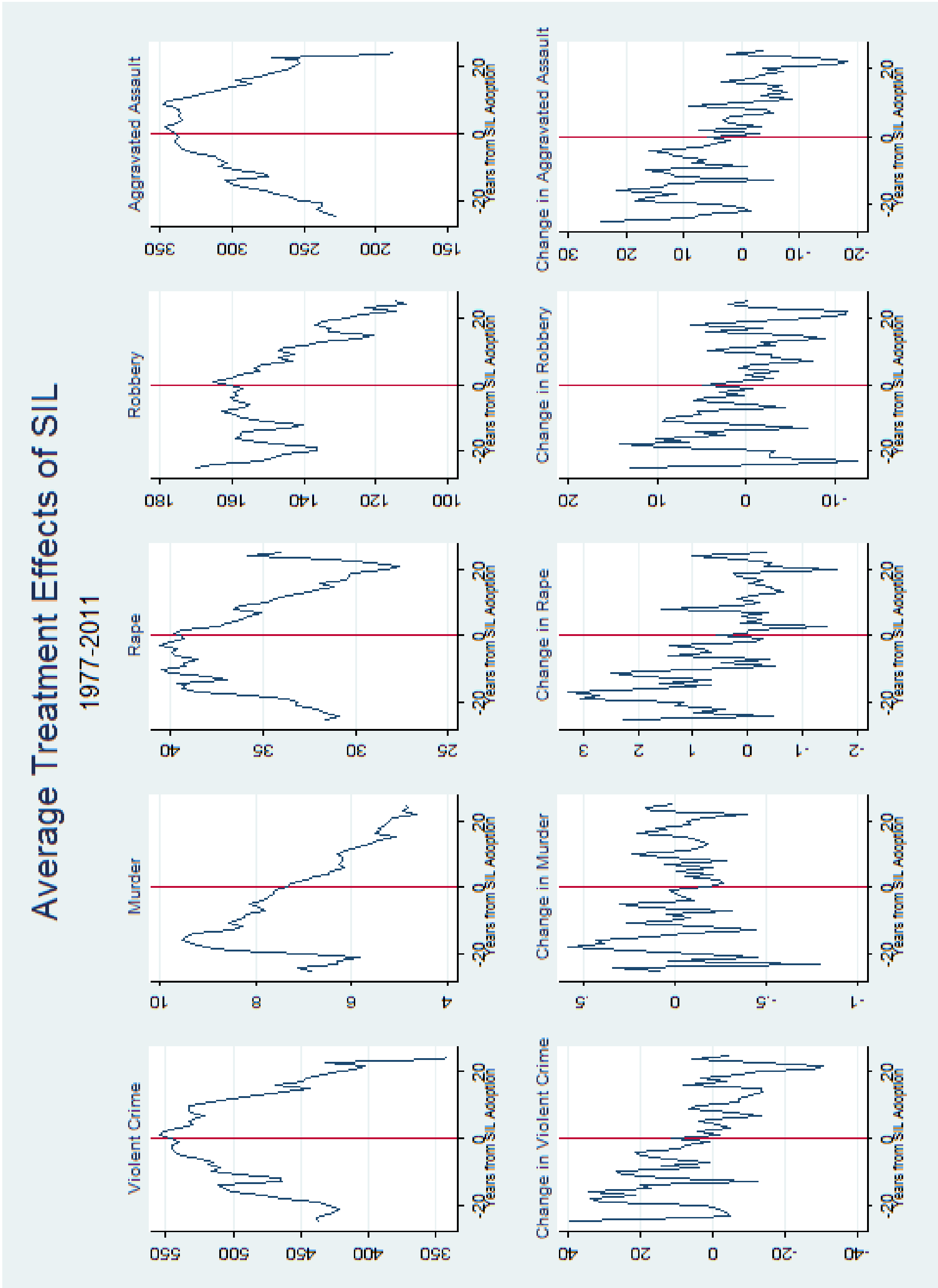
$$\Delta C_{st} = a + I_t^{Post} b + \epsilon_{st}. \tag{3}$$

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.

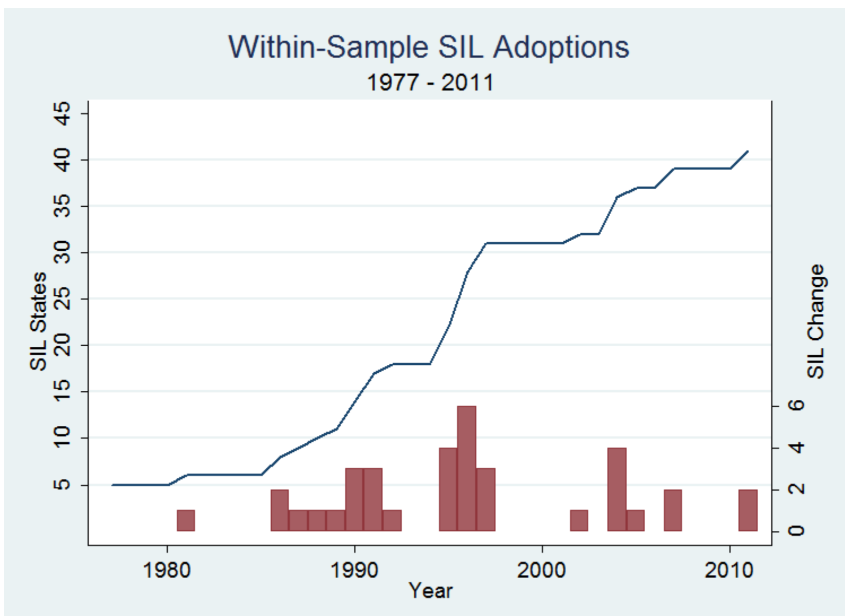
4 Graphical Evidence



In the first row, we graphed the population weighted average of crime rates across states centered around SIL adoption year. On average, we observe a decline in violent crime rates (across all categories) immediately following the adoption of SIL (although this phenomenon could be an artifact of the fact that most SIL adoption happened in 1990's, when national trend in crime rates is declining). The sudden change near the end of the sample is due to the fact that most states have dropped out of the sample by that time and thus the dataset is dominated by individual states. This will be addressed in the Robustness Checks section.

In the second row, we graphed the corresponding change in crime rates. Although generally exhibiting a downward trend, the changes in crime rates are more volatile and harder to see the treament effects of SIL although we do generally observe a slight downward trend immediately after the adoption of SIL.

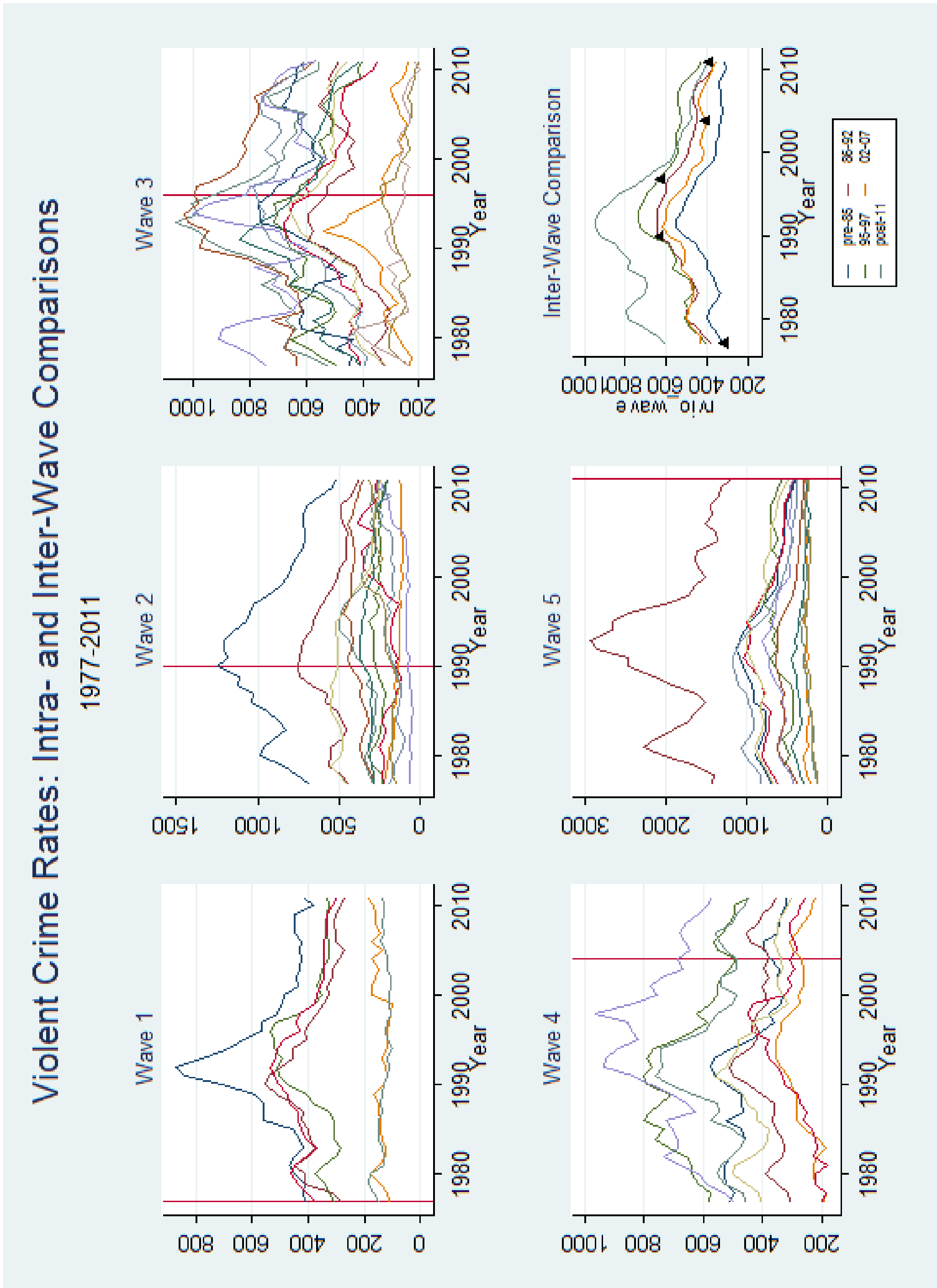
Now, instead of looking at the national average, we divided states into groups to further investigate any patterns in the data.

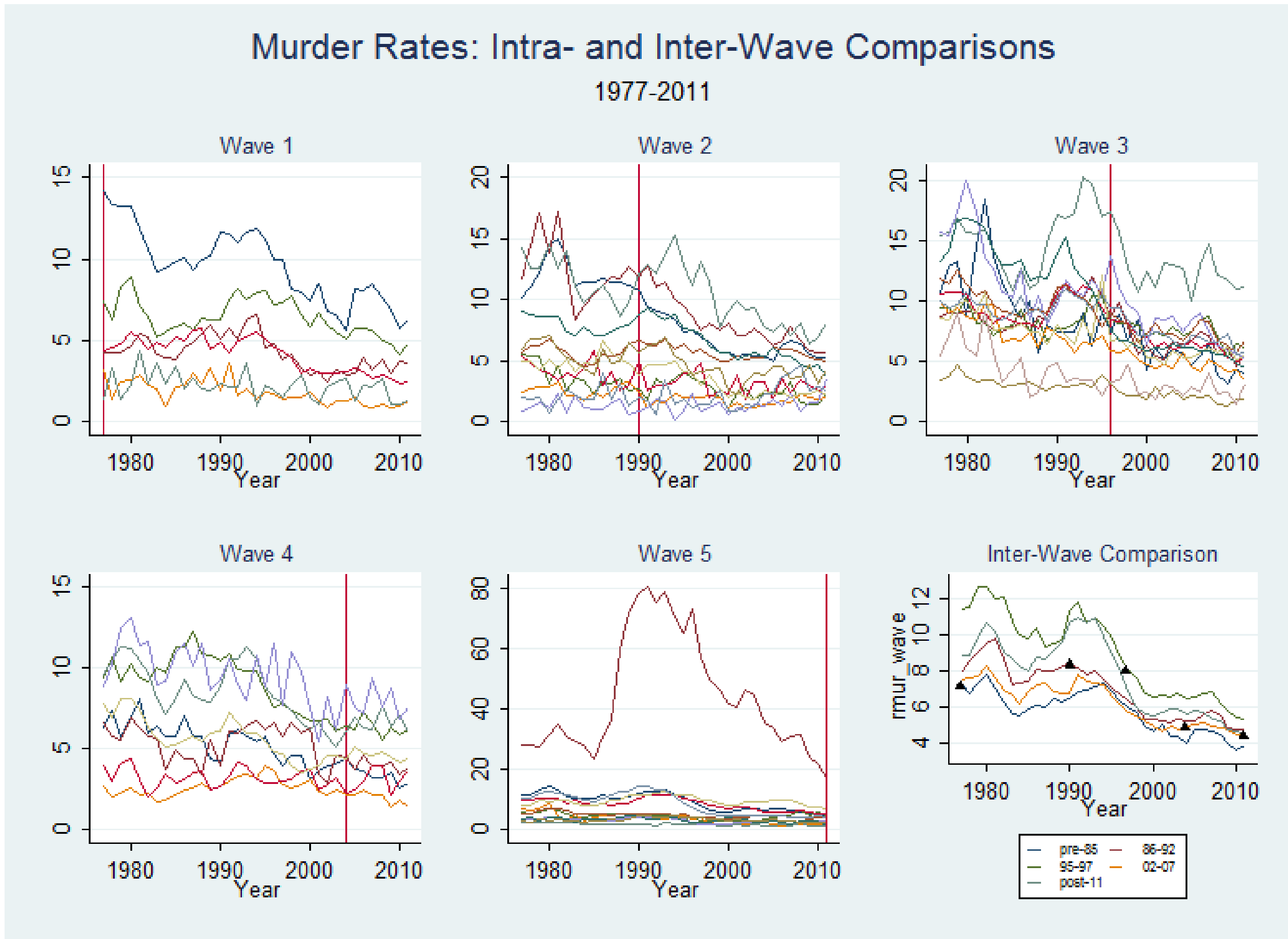


We graphed the total number of SIL states at any point in time within our sample (line) and the number of adoptions in each year (bar). It is evident from the graph above that adoptions can be divided into three distinct waves (Definition: pre-1985, 1986-1992, 1995-1997, 2002-2007, post-2011).

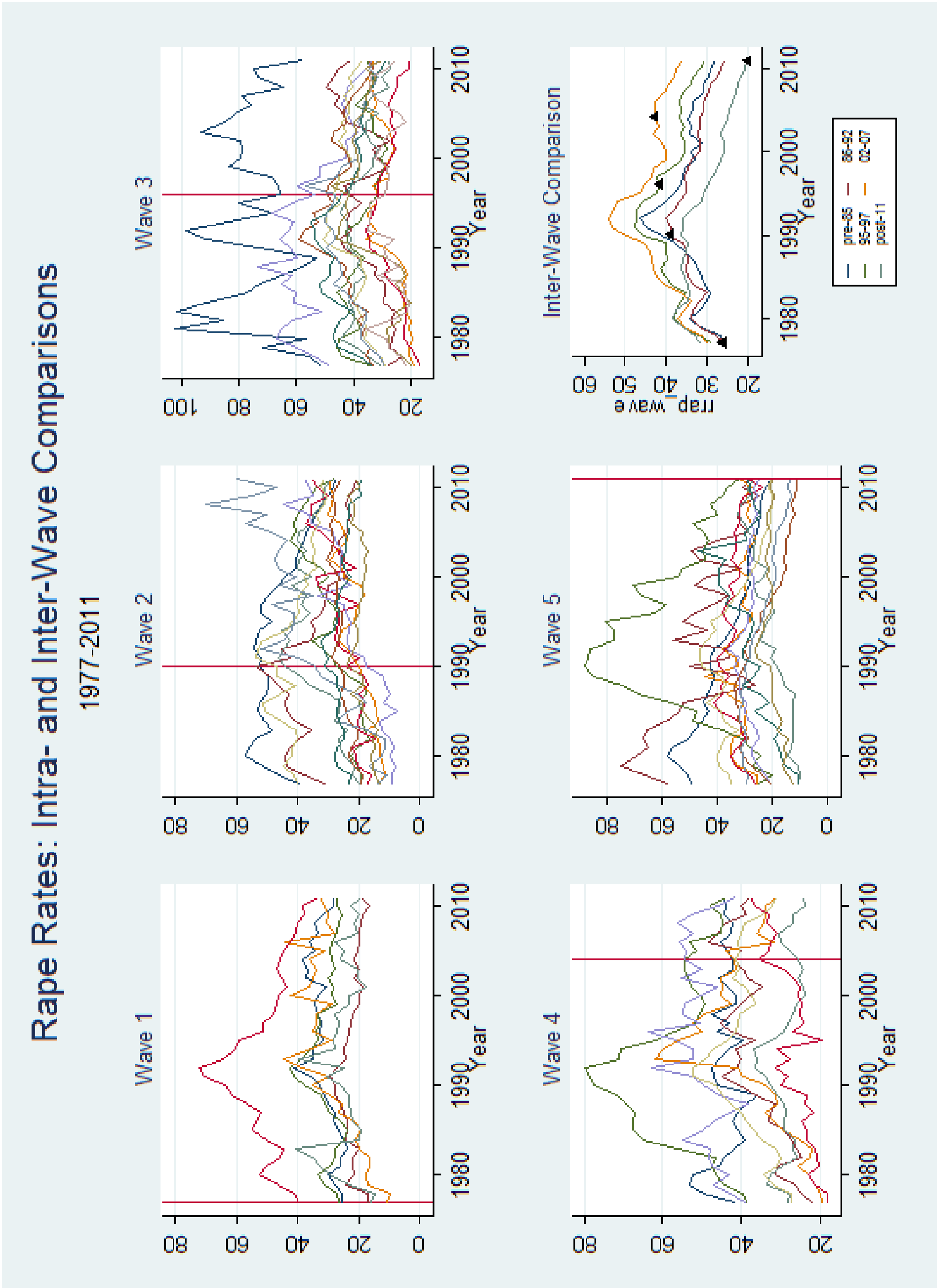
4.1 Within- and Across-Wave Comparisons

4.1.1 Level of Crime Rates

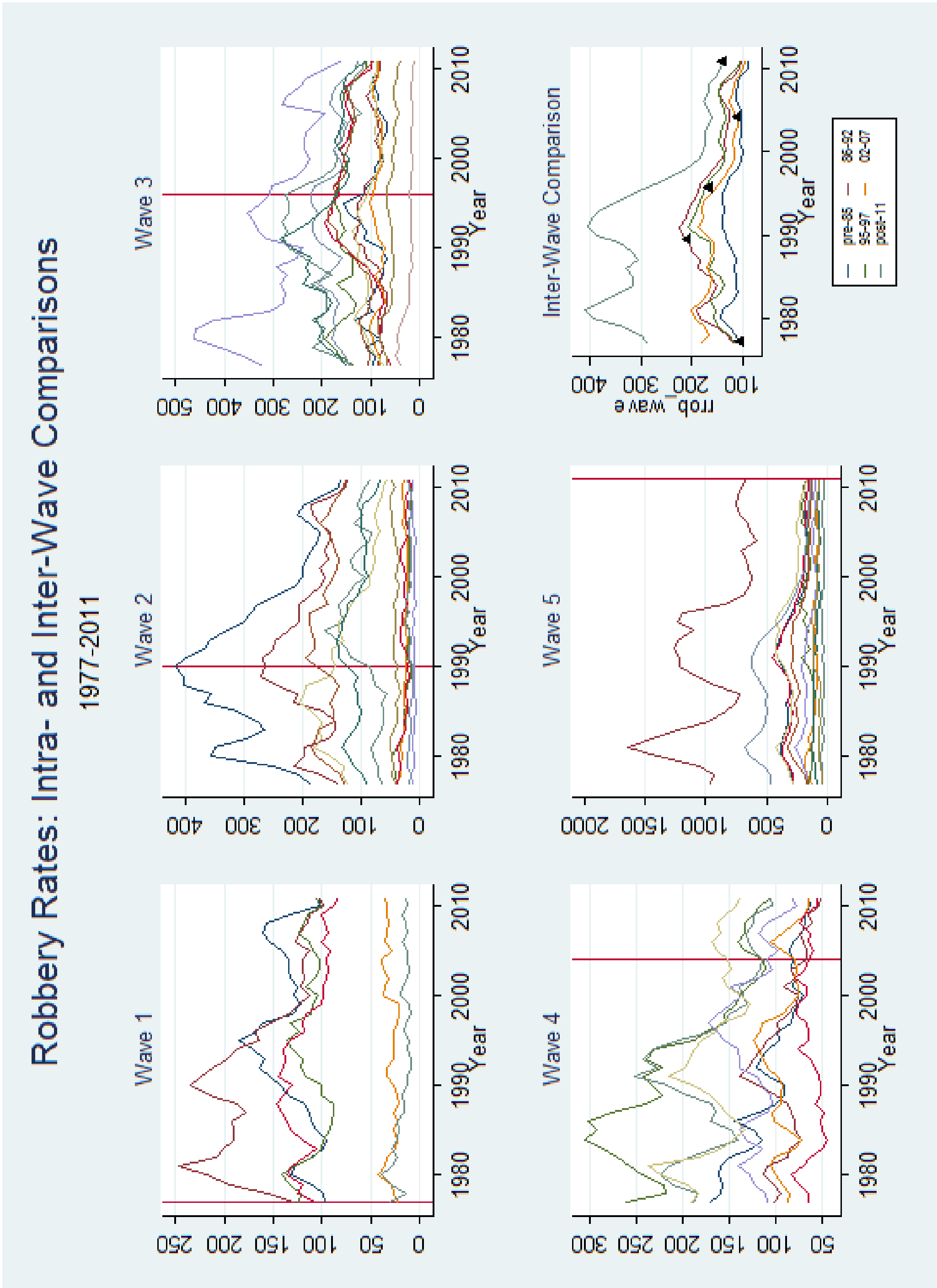




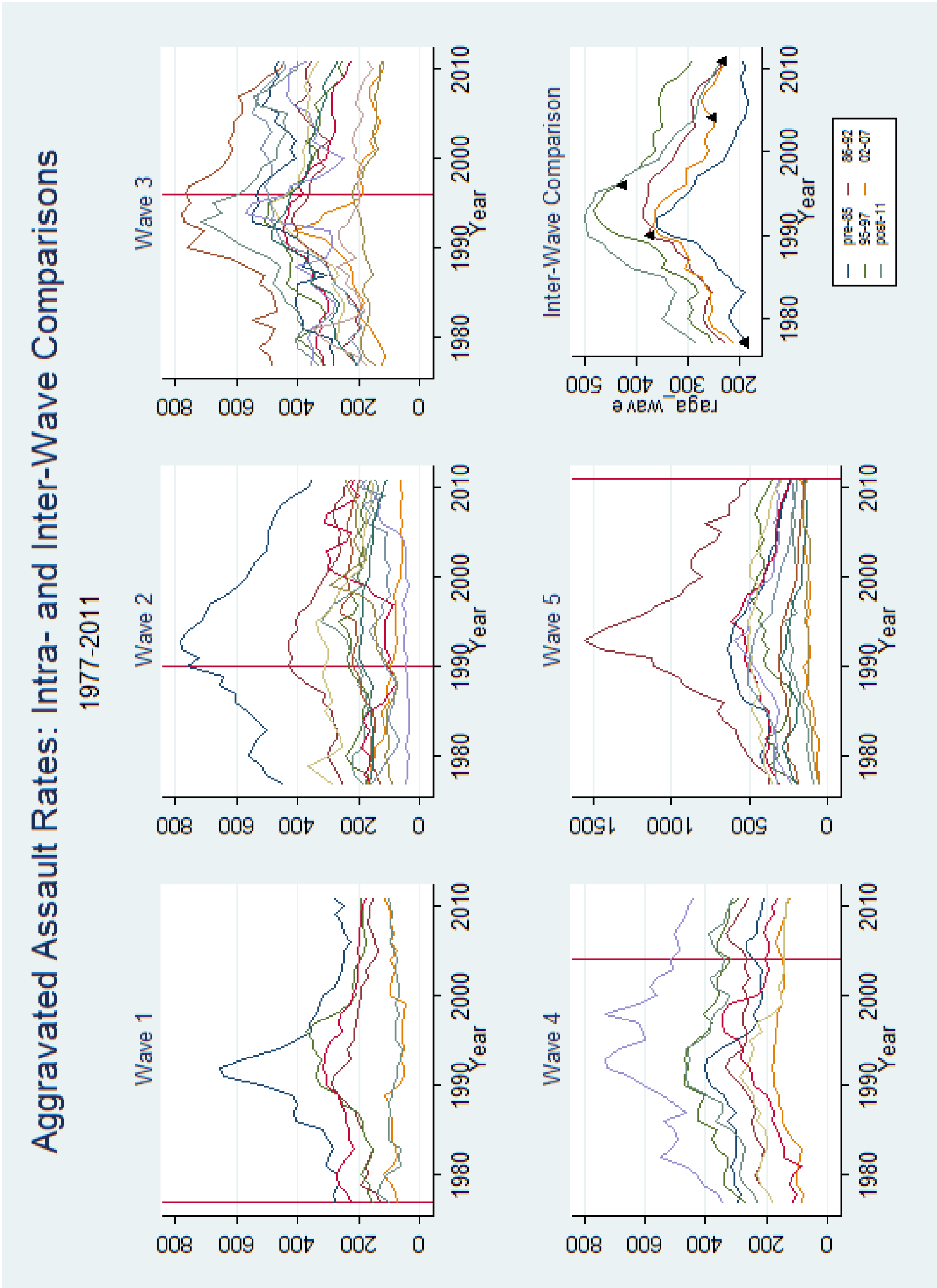
Murder Rates: Intra- and Inter-Wave Comparisons
1977-2011
Wave 1
Wave 2
Wave 3
Wave 4
Wave 5
Inter-Wave Comparison
Year
rmur_wave
pre-85
86-92
95-97
02-07
post-11



Rape Rates: Intra- and Inter-Wave Comparisons
1977-2011
Wave 1
Wave 2
Wave 3
Wave 4
Wave 5
Inter-Wave Comparison
Year
rrap_wave

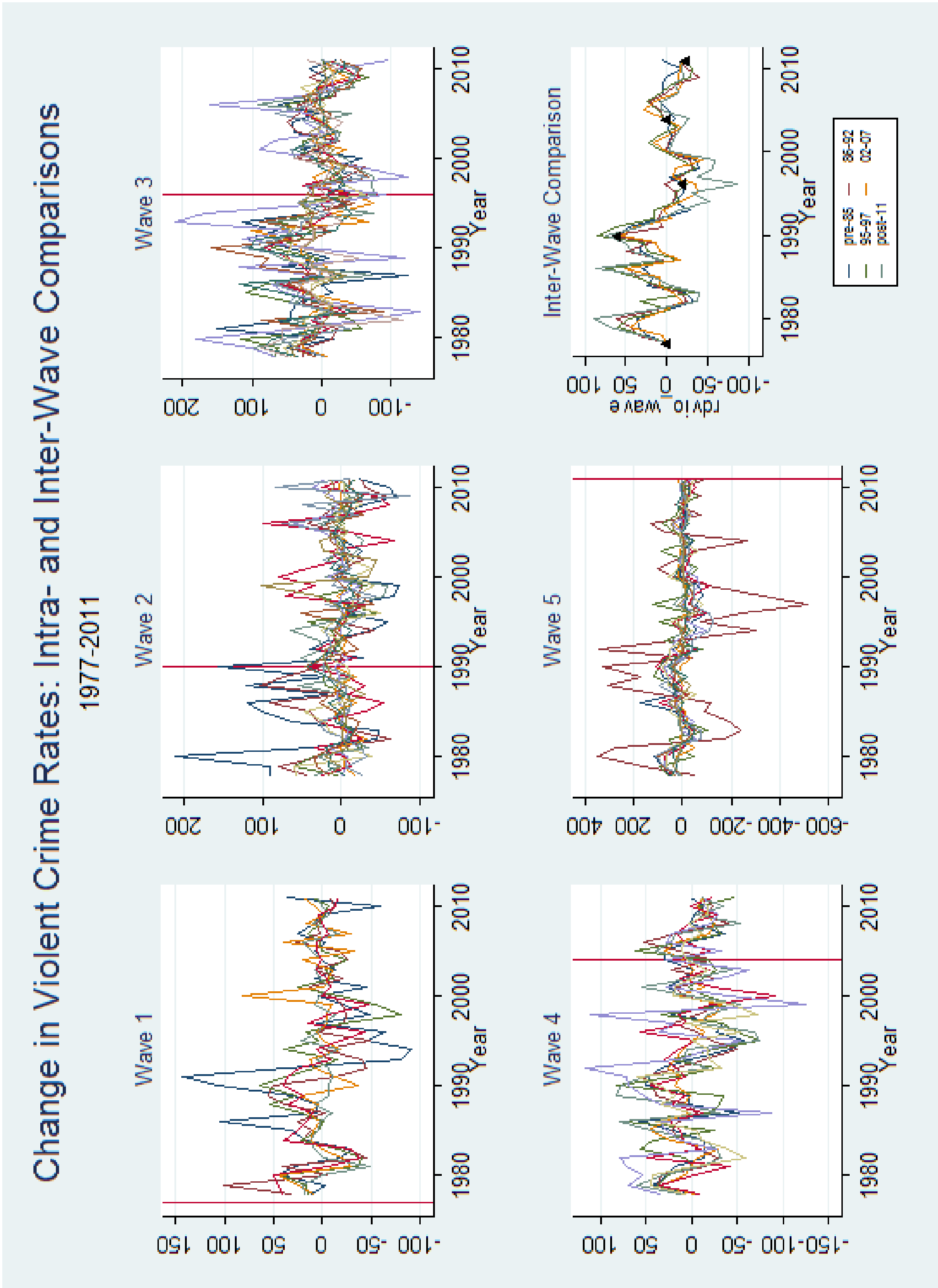


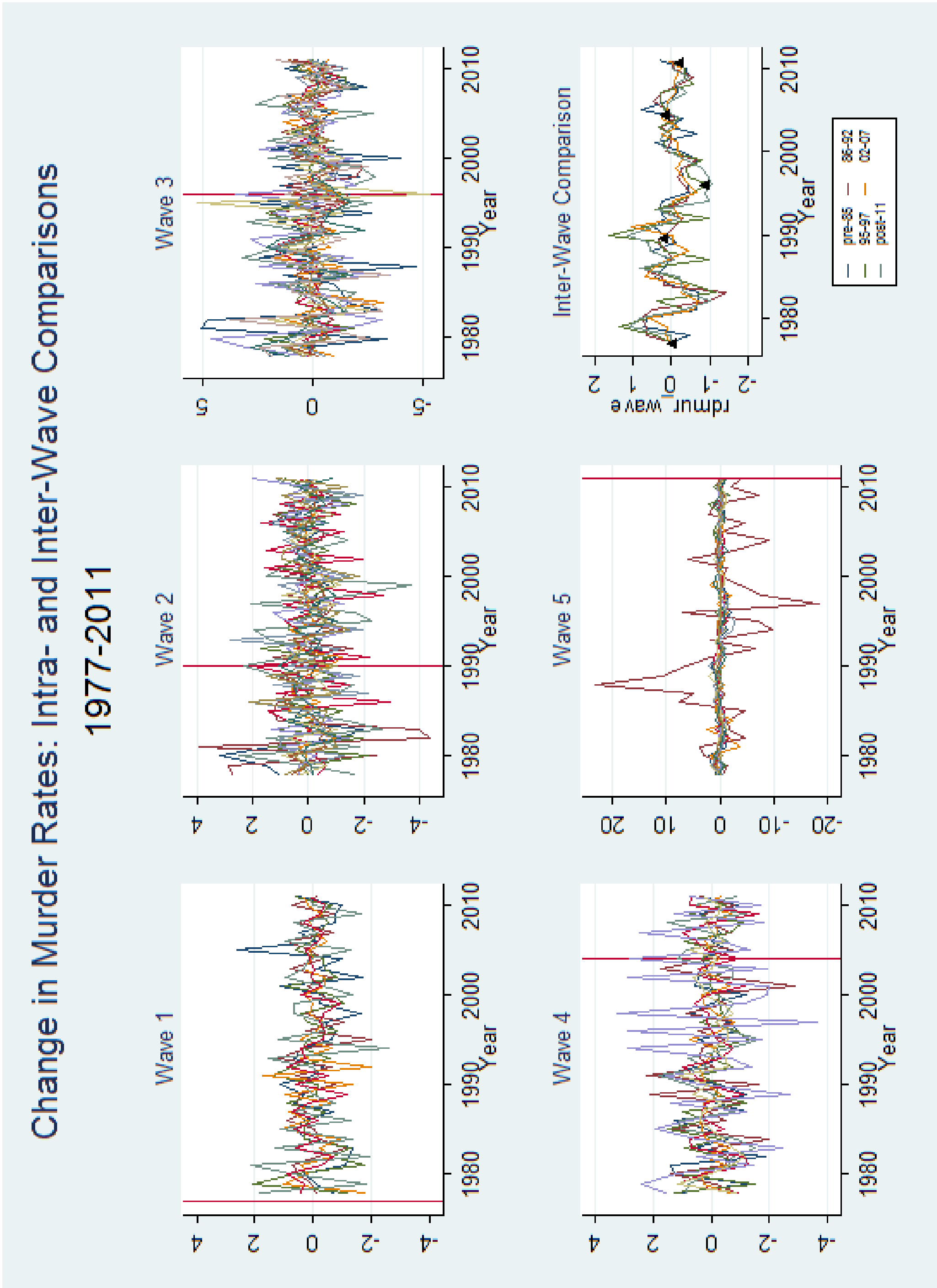
Robbery Rates: Intra- and Inter-Wave Comparisons
1977-2011
Wave 1
Wave 2
Wave 3
Wave 4
Wave 5
Inter-Wave Comparison
Year

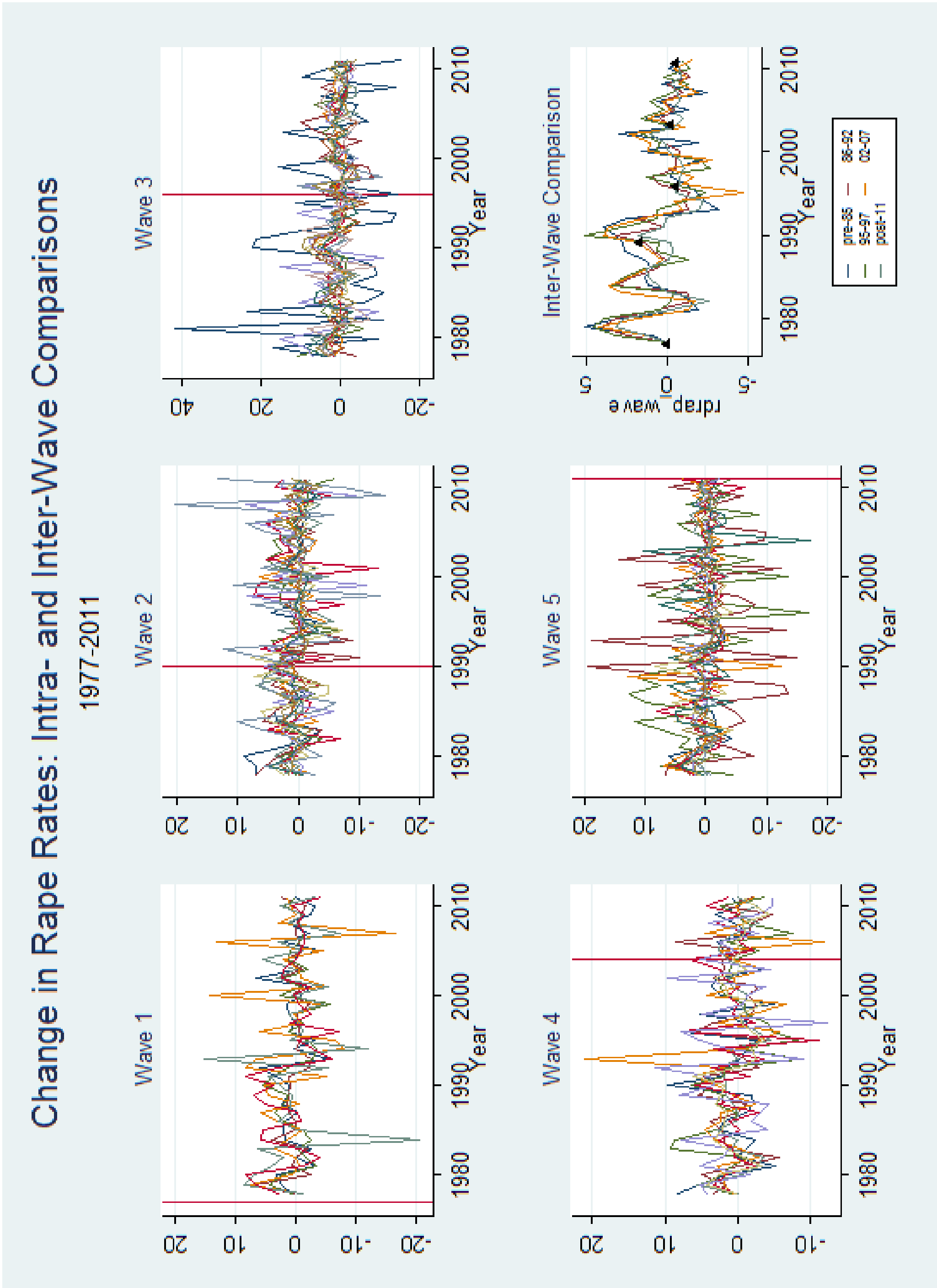


Aggravated Assault Rates: Intra- and Inter-Wave Comparisons
1977-2011
Wave 1
Wave 2
Wave 3
Wave 4
Wave 5
Inter-Wave Comparison
Year
raga_wave
pre-86
86-92
95-97
02-07
post-11

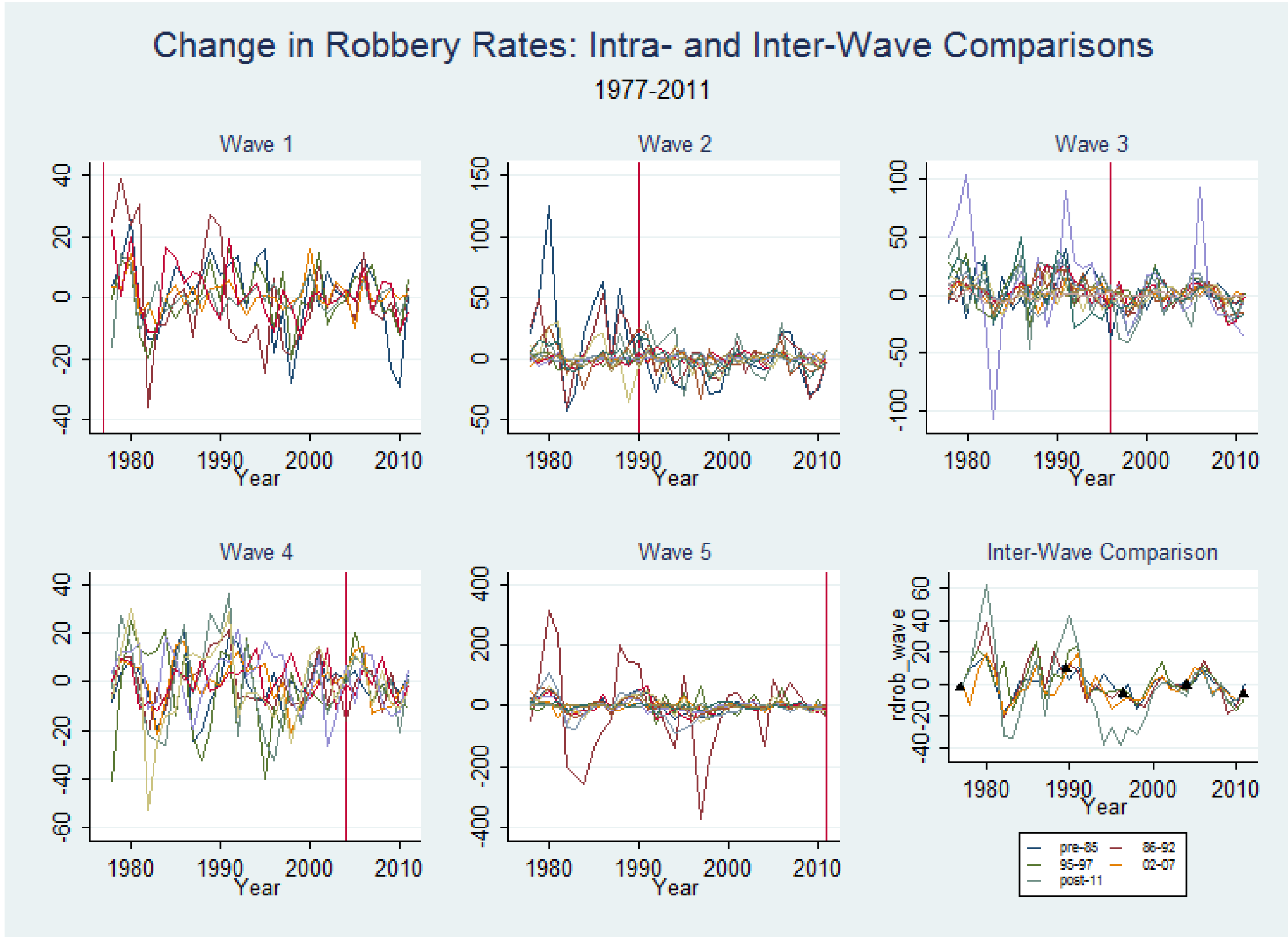
4.1.2 Change in Crime Rates

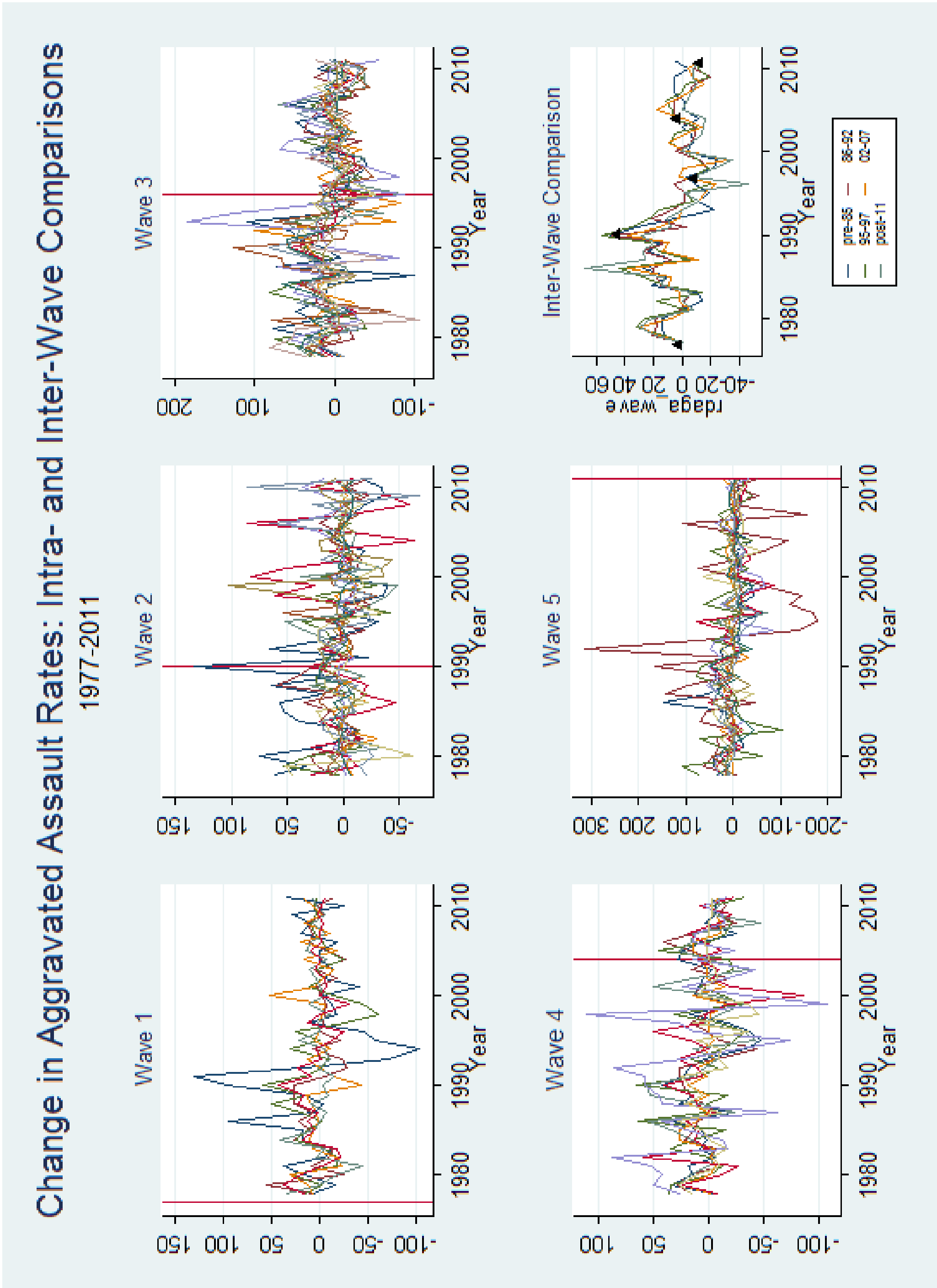



Change in Murder Rates: Intra- and Inter-Wave Comparisons
1977-2011
Wave 1
Wave 2
Wave 3
Wave 4
Wave 5
Inter-Wave Comparison
Year
rdmur_wave
pre-86
86-92
95-97
02-07
post-11



Change in Rape Rates: Intra- and Inter-Wave Comparisons
1977-2011
Wave 1
Wave 2
Wave 3
Wave 4
Wave 5
Inter-Wave Comparison
Year
rdrap_wave


Change in Robbery Rates: Intra- and Inter-Wave Comparisons
1977-2011
Wave 1
Wave 2
Wave 3
Wave 4
Wave 5
Inter-Wave Comparison
Year
rdrob_wave
pre-85
86-92
95-97
02-07
post-11


Change in Aggravated Assault Rates: Intra- and Inter-Wave Comparisons
1977-2011
Wave 1
Wave 2
Wave 3
Wave 4
Wave 5
Inter-Wave Comparison
Year
rdaga_wave
pre-85
86-92
93-97
02-07
post-11

4.1.3 Comments

From these graphs, we see that crime rates are primarily dominated by some national time trend from the high level of co-movement between waves. And thus, the adoption of SIL is only of second-order importance in explaining crime rates trends. Changes in crime rates are also noisier and follow less obvious patterns than levels of crime rates although between waves, they track each other more closely in the changes. Therefore, explaining crime changes by SIL is even harder, especially given the limitation of the available data, which at least partially explains the insignificance of our estimated CPDM coefficients later.

5 Naive Regressions

To further investigate statistical evidence of the effects of SIL adoption, we ran a set of naive regressions using the SIL dummy variable as the expanatory variable and only controlling for linear and quadratic state specific time trends, and state and year fixed effects. Different from the past researchers, we estimated a general least squares model with autocorrelated errors (Bertrand, Duflo, and Mullainathan (2004)).

To replicate Lott's results on the state level, we first restricted our sample to 1977 - 1992 and did not account for autocorrelated errors. (All the dependent variables are natural log of crime rates).

	lrvio	lrmur	lrrap	lrrob	lraga
shall	-.04445*	-.07428*	-.01232	.0096	-.08509***
	(.018)	(.03123)	(.02782)	(.03738)	(.01958)
Constant	6.0087***	2.0427***	3.2884***	4.9802***	5.3676***
	(.03149)	(.04174)	(.07476)	(.05082)	(.03684)
Observations	816	816	816	816	816

Standard errors in parentheses

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

As Lott has shown in his paper (1997), adoption of SIL reduces most of the violent crime categories including the violent crime index (results here are not exactly the same due to the use of state level data and controlling for state specific time trends).

However, when we accounted for autocorrelated errors:

	lrvio	lrmur	lrrap	lrrob	lraga
shall	-.02499	-.03911	-.01781	-.00045	-.02499
	(.01445)	(.02472)	(.01609)	(.01898)	(.01316)
Constant	5.6444***	2.4475***	3.159***	4.6249***	5.6941***
	(.24977)	(.04543)	(.06487)	(.17384)	(.18496)
Observations	816	816	816	816	816

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Although all the signs remain negative, any level of statistical significance was removed.

When we estimated on the full sample from 1977 - 2011 and accounted for autocorrelated errors:

	lrvio	lrmur	lrrap	lrrob	lraga
shall	.02811**	.01983	.0121	.04856***	.02054
	(.00918)	(.01578)	(.01097)	(.0135)	(.01067)
Constant	6.0296***	2.4677***	3.2482***	4.7881***	5.5072***
	(.07652)	(.03681)	(.16052)	(.19651)	(.06955)
Observations	1785	1785	1785	1785	1785

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The statistical evidence shows that, as Ayres and Donohue earlier (2003) suggested based on estimates from 1977 - 2006, SIL actually increases all categories of violent crime, where the positive effects were statistically significant in violent crime index and robbery (which is also the most intuitive crime category to be affected by SIL).

Then we repeated the same exercise on the log of change in crime rates. Again, we first presented results from Lott's model, where autocorrelated errors were not calculated and sample was from 1977 - 1992.

	lrdvio	lrdmur	lrdrap	lrdrob	lrdaga
shall	-.1175	162.96	-299.32	32.969	-83.707
	(.6448)	(359.35)	(190.23)	(25.627)	(70.425)
Constant	-1.5863	-1033.5	130.27	-31.364	18.396
	(3.3491)	(1636.2)	(288.79)	(53.09)	(40.401)
Observations	714	714	714	714	714

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Accounting for autocorrelated errors:

	lrdvio	lrdmur	lrdrap	lrdrob	lrdaga
shall	.08027	-51.723	-32.587	-3.2273	-15.731
	(.39113)	(111.57)	(40.841)	(6.4914)	(10.514)
Constant	.5675	-760.56	144.16	-20.62	11.356
	(1.6075)	(737.03)	(222.56)	(33.444)	(24.161)
Observations	714	714	714	714	714

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Full sample with autocorrelated errors:

	lrdvio	lrdmur	lrdrap	lrdrob	lrdaga
shall	.03996	-70.914	-12.957	.97736	.01563
	(.21392)	(62.118)	(15.07)	(3.5551)	(1.8934)
Constant	3.276**	-35.025	-50.461	-3.6073	.27545
	(1.024)	(343.74)	(97.917)	(19.953)	(8.8929)
Observations	1734	1734	1734	1734	1734

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

(DEPENDENT VARIABLE NAMES NEED TO BE CHANGED)

These results show that, as already indicated by the graphical evidence above, changes in crime rates are more volatile and not obviously affected by SIL.

6 Earlier Models

In this section, we present three main models proposed by past researchers. Again, we compare them with models corrected for autocorrelated errors and estimated with updated data.

6.1 Dummy Variable Model (Lott & Mustard)

In Lott and Mustard's original paper (1997), their main results came from this following simple differences-in-differences model where the main explanatory variable is just the SIL dummy variable. Note that in this model, they did not include any state specific time trends. In the second row of the following tables, arrests represent corresponding arrest rates for the respective dependent variables. Note that Lott and Mustard also laboriously (and blindly) controlled for 36 demographic groups by age and race, which are controlled for but not reported in the following tables. State and year fixed effects are also controlled but not reported. The first table exactly replicates Lott and Mustard's (1997) model (i.e. not accounting for autocorrelated errors and estimating on sample from 1977 - 1992):

	lrvio	lrmur	lrrap	lrrob	lraga
shall	-.09343***	-.03781	.01404	-.08587**	-.11583***
	(.0186)	(.03013)	(.02452)	(.02834)	(.02294)
arrests	-.01388	-.07837**	-.04099*	-.06698*	-.08422*
	(.02349)	(.02523)	(.01849)	(.0327)	(.03735)
rpcpi	2.0e-05***	5.6e-05***	1.8e-05**	1.5e-05	3.2e-05***
	(5.2e-06)	(7.9e-06)	(6.1e-06)	(8.4e-06)	(6.4e-06)
rpcrpo	-4.1e-05	-9.4e-05	-3.8e-05	-7.0e-05	8.4e-06
	(4.9e-05)	(7.4e-05)	(5.6e-05)	(7.0e-05)	(6.4e-05)
rpcui	-.00016	-.00014	-.00035***	-.00025	-2.1e-05
	(8.9e-05)	(.00011)	(8.7e-05)	(.00016)	(8.4e-05)
rpcim	.00011	1.9e-05	-4.6e-05	-.00025	.00047*
	(.00019)	(.00028)	(.00019)	(.00034)	(.00023)
stpop	5.0e-09	1.5e-07*	6.6e-08	-6.5e-09	9.9e-09
	(5.1e-08)	(7.2e-08)	(6.5e-08)	(8.3e-08)	(6.1e-08)
Constant	6.7262***	1.9027***	2.303***	6.3886***	5.37***
	(.36834)	(.53954)	(.44267)	(.63589)	(.47412)
Observations	810	807	807	809	810

Standard errors in parentheses

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

These results, similar to Lott and Mustard's findings, show significant and negative effects of the SIL dummy on multiple violent crime categories.

When accounting for autocorrelated errors, while still using the same sample up to 1992, we find similar but less significant results:

	lrvio	lrmur	lrrap	lrrob	lraga
shall	-.03624*	-.01148	.01479	-.05844**	-.0582**
	(.01551)	(.02489)	(.01605)	(.02119)	(.01798)
arrests	-.00715	-.07092***	-.02838*	-.02292	-.02981
	(.00914)	(.01315)	(.01326)	(.01413)	(.01556)
rpcpi	1.7e-05***	5.6e-05***	1.2e-05*	1.4e-05*	3.3e-05***
	(4.2e-06)	(5.6e-06)	(5.2e-06)	(6.1e-06)	(4.9e-06)
rpcrpo	-2.2e-06	-3.3e-05	-5.1e-05	6.4e-05	1.6e-05
	(3.3e-05)	(4.9e-05)	(4.1e-05)	(4.5e-05)	(3.8e-05)
rpcui	-3.9e-05	.00012	-.00023***	2.7e-05	-2.1e-05
	(5.9e-05)	(9.2e-05)	(6.4e-05)	(8.7e-05)	(6.1e-05)
rpcim	-.0002	-.00025	-.00012	-.00051*	.00026
	(.00015)	(.00021)	(.00015)	(.00021)	(.00016)
stpop	-3.5e-08	1.6e-07**	1.3e-09	-6.7e-08	-3.8e-08
	(4.0e-08)	(6.0e-08)	(4.5e-08)	(5.9e-08)	(4.3e-08)
Constant	6.6967***	1.5205***	2.0859***	4.8391***	6.1445***
	(.25496)	(.37167)	(.273)	(.39855)	(.27958)
Observations	810	807	807	809	810

Standard errors in parentheses

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

Then when we estimated the dummy variable model on the full sample, although most of the signs remained negative, any level of statistical significance was removed:

	lrvio	lrmur	lrrap	lrrob	lraga
shall	-.00311	.00855	-.00115	-.01444	-.00417
	(.00938)	(.0163)	(.0113)	(.01336)	(.01087)
arrests	-.01503	-.07678***	-.0515***	-.05179**	-.04888***
	(.0103)	(.01149)	(.01438)	(.01883)	(.01461)
rpcpi	-5.2e-06*	1.4e-05***	-7.1e-06**	-4.8e-06	-2.2e-06
	(2.3e-06)	(4.1e-06)	(2.7e-06)	(3.1e-06)	(2.9e-06)
rpcrpo	-1.0e-05	4.7e-05	-5.2e-05**	2.0e-05	-8.2e-06
	(1.6e-05)	(2.6e-05)	(2.0e-05)	(2.1e-05)	(1.9e-05)
rpcui	-3.2e-05	8.0e-05	-.00011*	4.7e-05	-7.2e-05
	(4.0e-05)	(7.7e-05)	(4.9e-05)	(5.8e-05)	(4.6e-05)
rpcim	-9.0e-05	-.00032**	-9.4e-05	-.00016	1.8e-05
	(5.8e-05)	(.00011)	(6.9e-05)	(8.6e-05)	(6.6e-05)
stpop	-6.1e-08*	2.5e-08	-8.8e-08**	1.5e-08	-8.5e-08**
	(2.4e-08)	(4.3e-08)	(2.9e-08)	(3.4e-08)	(2.9e-08)
Constant	6.2418***	2.5889***	3.7267***	5.3509***	5.6741***
	(.12584)	(.1595)	(.11474)	(.13969)	(.16566)
Observations	1753	1750	1750	1750	1753

Standard errors in parentheses

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

6.2 Spline Model (Lott & Mustard)

Lott and Mustard later proposed a spline model where they estimated state specific linear time trends before and after adoption of SIL and tested the difference between the two slopes. In the first table below, when estimating the spline model on the state level without autocorrelated errors and using the 1977 - 1992 sample, we actually found positive change in slopes from before to after the adoption of SIL.

	lrvio	lrmur	lrrap	lrrob	lraga
trnd_bf	.01455**	-.03073***	.03863***	-.00139	.00865
	(.00468)	(.00759)	(.00564)	(.00748)	(.00637)
trnd_af	.01826***	-.03231***	.03949***	-.00448	.01392
	(.00549)	(.00883)	(.00686)	(.00851)	(.00749)
arrests	-.01346	-.07789**	-.04133*	-.06225	-.08901*
	(.02351)	(.02491)	(.01865)	(.03256)	(.03806)
rpcpi	1.8e-05***	5.7e-05***	1.8e-05**	1.7e-05*	2.9e-05***
	(5.2e-06)	(8.3e-06)	(6.3e-06)	(8.7e-06)	(6.5e-06)
rpcrpo	-4.7e-05	-8.7e-05	-4.2e-05	-5.5e-05	2.6e-07
	(4.9e-05)	(7.4e-05)	(5.6e-05)	(7.0e-05)	(6.5e-05)
rpcui	-.00016	-.00013	-.00035***	-.00024	-2.6e-05
	(8.8e-05)	(.00011)	(8.7e-05)	(.00016)	(8.5e-05)
rpcim	9.3e-05	4.0e-06	-4.0e-05	-.00029	.00045
	(.00019)	(.00028)	(.00019)	(.00034)	(.00023)
stpop	8.5e-09	1.6e-07*	6.2e-08	8.1e-09	1.4e-08
	(5.0e-08)	(7.2e-08)	(6.5e-08)	(8.2e-08)	(6.2e-08)
Constant	11.395***	-8.1448**	14.924***	5.9244*	8.0845***
	(1.7363)	(2.7877)	(2.0152)	(2.8085)	(2.3389)
Observations	810	807	807	809	810

Standard errors in parentheses

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

Even with autocorrelated errors, the positive effects on the time trends still persist in most crime categories.

	lrvio	lrmur	lrrap	lrrob	lraga
trnd_bf	-.00334	.00131	-.00457	.00361	-.00367
	(.00244)	(.00294)	(.00346)	(.00382)	(.00305)
trnd_af	.00148***	.00088*	-.0008**	.00177***	.00177***
	(.00024)	(.00035)	(.00025)	(.00041)	(.00026)
arrests	-.0075	-.07058***	-.02904*	-.02098	-.03258*
	(.00924)	(.01316)	(.01334)	(.01401)	(.01592)
rpcpi	1.6e-05***	5.6e-05***	1.1e-05*	1.4e-05*	3.0e-05***
	(4.2e-06)	(5.9e-06)	(5.3e-06)	(6.3e-06)	(4.9e-06)
rpcrpo	-5.4e-06	-3.4e-05	-5.3e-05	6.8e-05	-6.7e-07
	(3.3e-05)	(5.0e-05)	(4.1e-05)	(4.5e-05)	(3.8e-05)
rpcui	-4.2e-05	.00011	-.00023***	3.8e-05	-2.8e-05
	(5.8e-05)	(9.2e-05)	(6.4e-05)	(8.7e-05)	(6.1e-05)
rpcim	-.0002	-.00024	-.00012	-.0005*	.00019
	(.00015)	(.00021)	(.00015)	(.00021)	(.00015)
stpop	-3.6e-08	1.6e-07**	-1.0e-09	-5.9e-08	-4.5e-08
	(3.9e-08)	(5.9e-08)	(4.6e-08)	(5.9e-08)	(4.3e-08)
Constant	5.2574***	.63898***	2.871***	3.0413***	4.6059***
	(.11046)	(.16376)	(.13503)	(.24524)	(.12918)
Observations	810	807	807	809	810

Standard errors in parentheses

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

However, when we estimated the spline model on the full sample, most of the signs were fipped, suggesting a negative effect of SIL on crime trends.

	lrvio	lrmur	lrrap	lrrob	lraga
trnd_bf	.00401**	.00574**	.00126	-.00068	.00557**
	(.00149)	(.00182)	(.00149)	(.00195)	(.0019)
trnd_af	.00073***	.0014***	.00046***	.0022***	.00051**
	(.00014)	(.00016)	(.00011)	(.00019)	(.00019)
arrests	-.01448	-.07556***	-.0522***	-.05141**	-.04785**
	(.01026)	(.01151)	(.0144)	(.01857)	(.01457)
rpcpi	-5.5e-06*	1.4e-05***	-6.6e-06*	-4.4e-06	-1.8e-06
	(2.3e-06)	(4.1e-06)	(2.8e-06)	(3.1e-06)	(2.9e-06)
rpcrpo	-9.8e-06	5.1e-05*	-5.0e-05*	2.1e-05	-7.2e-06
	(1.6e-05)	(2.6e-05)	(2.0e-05)	(2.1e-05)	(1.9e-05)
rpcui	-3.5e-05	8.2e-05	-.00011*	4.9e-05	-7.3e-05
	(4.0e-05)	(7.7e-05)	(4.9e-05)	(5.8e-05)	(4.6e-05)
rpcim	-9.5e-05	-.00032**	-9.6e-05	-.00014	1.8e-05
	(5.8e-05)	(.00011)	(6.9e-05)	(8.6e-05)	(6.6e-05)
stpop	-6.1e-08*	2.3e-08	-8.4e-08**	1.7e-08	-8.6e-08**
	(2.4e-08)	(4.3e-08)	(2.9e-08)	(3.4e-08)	(2.9e-08)
Constant	5.5814***	1.3121***	3.2673***	3.1352***	5.2354***
	(.10845)	(.13211)	(.08213)	(.16601)	(.13241)
Observations	1753	1750	1750	1750	1753

Standard errors in parentheses

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

Hence, we see that the in the dummy variable model, effect of SIL on crime rates changed from negative to positive when we changed from the subsample to full sample. On the other hand, in the spline model, effect of SIL on the crime trends changed in the opposite direction.

6.3 Hybrid Model (Ayres & Donohue)

Ayres and Donohue (2003) proposed a less restrictive hybrid model where both SIL dummy and state specific time trends were estimated.

	lrvio	lrmur	lrrap	lrrob	lraga
trnd_bf	.01665***	-.02992***	.03834***	.00042	.01127
	(.0047)	(.00761)	(.00564)	(.00767)	(.0062)
shall	-.0972***	-.03702	.01354	-.08444**	-.12097***
	(.01866)	(.0298)	(.02449)	(.0282)	(.02241)
trnd_af	.02172***	-.03097***	.039***	-.00148	.01823*
	(.00552)	(.00881)	(.00685)	(.0088)	(.00731)
arrests	-.0143	-.07833**	-.04129*	-.06645*	-.08896*
	(.02418)	(.02527)	(.0186)	(.03251)	(.03797)
rpcpi	1.7e-05**	5.6e-05***	1.8e-05**	1.6e-05	2.8e-05***
	(5.1e-06)	(8.3e-06)	(6.3e-06)	(8.7e-06)	(6.4e-06)
rpcrpo	-5.7e-05	-9.1e-05	-4.0e-05	-6.4e-05	-1.2e-05
	(5.0e-05)	(7.4e-05)	(5.6e-05)	(7.1e-05)	(6.4e-05)
rpcui	-.00017	-.00014	-.00035***	-.00024	-3.8e-05
	(8.8e-05)	(.00011)	(8.7e-05)	(.00016)	(8.4e-05)
rpcim	.00012	1.5e-05	-4.4e-05	-.00026	.00049*
	(.00019)	(.00028)	(.00019)	(.00034)	(.00023)
stpop	-4.3e-09	1.5e-07*	6.4e-08	-3.0e-09	-2.3e-09
	(5.1e-08)	(7.2e-08)	(6.5e-08)	(8.3e-08)	(6.1e-08)
Constant	12.109***	-7.8671**	14.824***	6.5429*	8.9794***
	(1.741)	(2.7973)	(2.0117)	(2.87)	(2.2846)
Observations	810	807	807	809	810

Standard errors in parentheses

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

	lrvio	lrmur	lrrap	lrrob	lraga
trnd_bf	-.00349	.00098	-.00418	.00301	-.0049
	(.00228)	(.00296)	(.00347)	(.00373)	(.00283)
shall	-.03657*	-.01164	.01342	-.05809**	-.06006***
	(.01535)	(.02493)	(.01609)	(.02124)	(.0178)
trnd_af	.00148***	.00091*	-.0008**	.00183***	.00179***
	(.00024)	(.00036)	(.00025)	(.00041)	(.00026)
arrests	-.00765	-.07087***	-.02927*	-.02269	-.03413*
	(.0092)	(.01317)	(.01333)	(.01408)	(.01581)
rpcpi	1.5e-05***	5.6e-05***	1.1e-05*	1.4e-05*	3.1e-05***
	(4.2e-06)	(5.9e-06)	(5.3e-06)	(6.3e-06)	(4.9e-06)
rpcrpo	-6.1e-06	-3.4e-05	-5.2e-05	6.4e-05	3.8e-06
	(3.3e-05)	(5.0e-05)	(4.1e-05)	(4.5e-05)	(3.8e-05)
rpcui	-5.3e-05	.00012	-.00023***	2.8e-05	-3.6e-05
	(5.9e-05)	(9.2e-05)	(6.4e-05)	(8.7e-05)	(6.2e-05)
rpcim	-.0002	-.00025	-.00013	-.00051*	.00021
	(.00015)	(.00021)	(.00015)	(.00021)	(.00016)
stpop	-4.3e-08	1.6e-07**	3.0e-10	-6.5e-08	-5.7e-08
	(3.9e-08)	(6.0e-08)	(4.5e-08)	(5.9e-08)	(4.4e-08)
Constant	5.2564***	.63588***	2.8798***	3.03***	4.5594***
	(.11109)	(.16427)	(.13404)	(.24638)	(.12816)
Observations	810	807	807	809	810

Standard errors in parentheses

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

	lrvio	lrmur	lrrap	lrrob	lraga
trnd_bf	.00397**	.0057**	.00134	-.00089	.00572**
	(.0015)	(.00184)	(.0015)	(.00192)	(.00191)
shall	-.00471	.00621	-.00209	-.01315	-.00712
	(.0094)	(.01635)	(.01135)	(.01336)	(.0109)
trnd_af	.00074***	.00139***	.00047***	.0022***	.00051**
	(.00014)	(.00016)	(.00011)	(.00018)	(.00019)
arrests	-.01468	-.07536***	-.0521***	-.05191**	-.04771**
	(.01031)	(.01152)	(.01443)	(.01882)	(.01458)
rpcpi	-5.6e-06*	1.5e-05***	-6.5e-06*	-4.8e-06	-1.9e-06
	(2.3e-06)	(4.1e-06)	(2.8e-06)	(3.1e-06)	(2.9e-06)
rpcrpo	-1.0e-05	4.9e-05	-4.9e-05*	1.9e-05	-7.3e-06
	(1.6e-05)	(2.6e-05)	(2.0e-05)	(2.1e-05)	(1.9e-05)
rpcui	-3.5e-05	8.1e-05	-.00011*	5.0e-05	-7.3e-05
	(4.0e-05)	(7.7e-05)	(4.9e-05)	(5.8e-05)	(4.6e-05)
rpcim	-9.4e-05	-.00032**	-9.5e-05	-.00015	2.0e-05
	(5.8e-05)	(.00011)	(6.9e-05)	(8.6e-05)	(6.6e-05)
stpop	-6.1e-08*	2.3e-08	-8.6e-08**	1.6e-08	-8.5e-08**
	(2.4e-08)	(4.3e-08)	(2.9e-08)	(3.4e-08)	(2.9e-08)
Constant	5.5825***	1.3035***	3.2666***	3.1377***	5.2418***
	(.10652)	(.13281)	(.0828)	(.16337)	(.13174)
Observations	1753	1750	1750	1750	1753

Standard errors in parentheses

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

7 Estimated CPDM

7.1 Without Controls

	lrdvio	lrdmur	lrdrap	lrdrob	lrdaga
entry_base	7.099	-532.67	533.2	49.174	-53.929
	(13.729)	(1892)	(974.36)	(203.61)	(134.63)
entry_SIL	-.87221	-721.49*	51.35	15.09	10.178
	(2.5494)	(361.13)	(177.11)	(37.489)	(28.553)
exit_base	-.01899	-12.865	4.3405	.61921	-.16538
	(.01451)	(68.156)	(15.343)	(1.1584)	(.19121)
selection	-.00053	23.393	1.1455	.20726	-.00148
	(.00333)	(21.553)	(4.6568)	(.34693)	(.05667)
surprise0_1	.0019	23.155	-1.7335	-.07329	-.01429
	(.00276)	(13.951)	(3.0668)	(.26927)	(.04099)
surprise2_4	.00067	27.811*	-1.7487	-.12472	-.01823
	(.00276)	(14.153)	(3.0395)	(.26789)	(.04224)
surprise5_9	.00166	16.547	-1.4585	-.17621	-.01447
	(.00285)	(14.78)	(3.2107)	(.29589)	(.04436)
surprise10_19	.00131	25.908	-4.2824	-.12421	-.01651
	(.00356)	(17.679)	(4.1274)	(.41985)	(.05367)
surprise20	-.00361	36.587	-11.878	-.58348	-.01301
	(.00661)	(37.923)	(9.4518)	(1.074)	(.10792)
Observations	1581	1581	1581	1581	1581

Standard errors in parentheses

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

7.2 With Controls

	lrdvio	lrdmur	lrdrap	lrdrob	lrdaga
entry_base	15.82	-4363.8	1229.8	1898	-746.51
	(19.46)	(8386.3)	(7787.4)	(1455.4)	(729.98)
entry_SIL	1.0377	-3352.7	-417.09	-209.45	125.1
	(3.5142)	(1913.8)	(684.43)	(145.83)	(82.814)
exit_base	-.02049	120.76	-63.819	6.2207	-1.2293
	(.02136)	(336.04)	(124.25)	(5.0029)	(.92753)
selection	.00327	87.109	-3.9145	2.4377*	-.24344
	(.00448)	(84.715)	(11.172)	(1.1121)	(.21781)
surprise0_1	.00055	107.03	.02683	.26276	-.24327
	(.0036)	(67.582)	(10.032)	(1.0669)	(.14164)
surprise2_4	.00045	108.38	-1.2365	1.482	-.24253
	(.00405)	(60.186)	(9.924)	(.89393)	(.15507)
surprise5_9	.00207	77.081	-1.5354	1.5991	-.24399
	(.00391)	(54.576)	(11.202)	(.94111)	(.16676)
surprise10_19	.00161	70.494	-9.5242	2.5821	-.34787
	(.00472)	(47.112)	(12.568)	(1.5524)	(.2371)
surprise20	-.00578	69.218	-25.399	.63519	-.56358
	(.00794)	(63.404)	(21.804)	(2.3838)	(.46451)
Observations	1549	1548	1547	1546	1549

Standard errors in parentheses

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

	lrdvio	lrdmur	lrdrap	lrdrob	lrdaga
entry_base	17.709	-1522.9	434.36	55.125	-70.115
	(14.605)	(2132.9)	(1361.3)	(253.22)	(138.54)
entry_SIL	.98397	-879.31*	-47.23	12.026	23.476
	(2.5888)	(391.49)	(235.48)	(40.68)	(28.055)
exit_base	-.01371	-39.699	2.8009	.73461	-.216
	(.01483)	(76.166)	(22.054)	(1.3751)	(.19973)
selection	-.00043	27.231	2.009	.21213	-.00887
	(.00344)	(19.441)	(6.0078)	(.37671)	(.05398)
surprise0_1	9.3e-05	27.612	.03892	-.06767	-.0309
	(.0028)	(14.799)	(4.0911)	(.29104)	(.04002)
surprise2_4	-.00102	31.603*	.1178	-.1101	-.03608
	(.00279)	(14.725)	(4.0577)	(.28665)	(.04119)
surprise5_9	.00049	20.315	-.22035	-.15372	-.02859
	(.00288)	(15.514)	(4.3018)	(.31563)	(.04257)
surprise10_19	.0008	26.201	-2.4716	-.09091	-.03129
	(.00355)	(18.549)	(5.4201)	(.44537)	(.051)
surprise20	-.00141	36.895	-9.0618	-.51281	-.02484
	(.00662)	(36.27)	(11.998)	(1.1394)	(.10317)
Observations	1549	1548	1547	1546	1549

Standard errors in parentheses

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

8 Robustness Checks

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