Prison Crowding and Violent Misconduct

Jonathan Kurzfeld*

November 3, 2017

Abstract

Justice reform has recently become a popular bipartisan topic in U.S. politics, with reducing the burgeoning U.S. prison population as one of the primary goals. The objective of this research is to estimate the causal relationship between prison crowding and violent behavior. Understanding this relationship is crucial to evaluating the costs of having severely overcrowded prisons as well as the benefits of reducing such crowding. This study exploits exogenous variation in California prison populations, resulting from a Supreme Court mandate to reduce prison crowding, to estimate the effect on violence. Using both difference-in-differences and instrumental variables identification strategies, a significant positive relationship is identified that is robust to a variety of model specifications. The estimates suggest that reducing prison crowding by 10 percentage points leads to a reduction in the rate of assault and battery of approximately $12\% - 15\%$. These estimates represent the first in the literature to directly estimate the effect of prison crowding on violent misconduct and do so using a quasi-experimental design. Furthermore, heterogeneity of point estimates across treated subpopulations is discussed as evidence of compositional change associated decreasing prison crowding.

JEL Codes: K14, K42, D03, A12

Job Market Paper

– Special thanks to the Presley Center for Crime and Justice Studies and the University of California Consortium on Social Science and Law for their generous support of this research. Additional thanks to Richard Arnott, Joseph Cummins, Mindy Marks, Michael Bates, Gregory DeAngelo, and department colleagues for their invaluable contributions to this work. –

*Department of Economics, 3123 Sproul Hall, University of California, Riverside; email: jkurzfeld@gmail.com.

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1 Introduction

"The degree of civilization in a society can be measured by entering its prisons."

– Fyodor Dostoevsky –

The issue of interpersonal violence within prisons is endemic to the administration of justice. The fundamental nature of the problem is evidenced by the fact that it can be observed throughout history and across numerous cultures, ideologies, and nations. A study in the U.K. found that roughly half of inmates reported having been both bully and victim while incarcerated (South & Wood, 2006). Meanwhile a simple web search for the world's most violent prisons will turn up numerous lists that include prisons on every continent and in nations that are rich and poor, developing and industrialized, and of every religious association[1]. Given the function of prisons within a system of justice, the pervasive nature of violence is no great surprise. Nevertheless, it is generally held that violence within the prison setting is not an intended element of the sanctions imposed by the judiciary. This position has been affirmed on several occasions by the U.S. Supreme Court and legal scholars have further argued that violence in prison should be viewed as an infringement on the human rights of those subjected to incarceration (White, 2008). The preceding implies that a civilized society must take measures to minimize the presence of prison violence, even in the absence of direct institutional benefits from doing so.

Yet there are clear fiscal benefits to effectively managing prison violence. This is especially true in the United States, known to be the most incarcerated nation in the world. Recent estimates have the U.S. spending approximately \$80 billion per year on incarceration and as much as \$8.2 billion[2] on prison healthcare alone (Glaze and Haberman, 2013). Although only a fraction of the latter cost is a direct result of violence, there are a host of additional costs associated with violence, from disability for injured guards to the cost of extending sentences for inmates convicted of new crimes.

Not surprisingly prison violence has drawn a great deal of attention from academic researchers seeking to identify individual and institutional characteristics that correlate with violent behavior. Prison crowding is among the most common institutional characteristics examined but is not a

[1]Some examples of such lists are here and here.

[2]Report by the PEW Trusts and MacArthur Foundation found here.

consistent correlate of violence (Franklin, Franklin, & Pratt, 2006). This paper is the first in this literature to both adopt a quasi-experimental design and directly estimate the relationship between prison crowding and violent behavior. The two questions posed in this research are, is there a causal relationship between crowding and prison violence? And, if so, why has previous research struggled to provide consistent evidence of such a relationship?

The quasi-experimental design used in this paper relies on a court mandated reduction in the overall level of crowding in California prisons. On May 23, 2011, California was placed under court order by the U.S. Supreme Court to reduce its prison population to 137.5% of design capacity or less within a two year period[3]. This resulted in the enactment of new legislation that drastically reduced the flow of inmates into California correctional facilities, creating a plausibly exogenous shock to the levels of crowding in California prisons. This legislation is referred to as California Public Safety Realignment or simply AB 109 (henceforth as the latter).

The exogeneity of the shock to crowding is critical to identifying a causal relationship between crowding and violence because, above and beyond the typical omitted variable concerns, there remains a plausible simultaneity problem in this setting. Suppose that administrators believe the crowdedness of a facility does lead to more violent behavior from the inmates, and therefore new inmates are directed away from facilities that have had recent issues with violence. Then more crowdedness may lead to more violence, but more violence also leads to less crowdedness. This simultaneity will depress naive estimates of the effect of crowding on violence and therefore cause a bias towards zero, assuming the true causal relationship is indeed positive.

Two estimation strategies are used to exploit the exogenous variation created by AB 109, both using monthly observations of 30 California prisons over more than four years. The first is a straightforward difference in differences strategy, with the added dimension that several treatments are estimated simultaneously to account for the distinct way in which AB 109 impacted different types of inmate populations. The second strategy is an instrumental variables approach that uses the time intensity of the policy's effect on crowding, in conjunction with differences in the mix of population types prior to the shock, to predict changes in crowding. Those predictions are then used in the second stage regression to estimate the marginal effect of crowding on the rate of assaults. The two approaches provide robust, statistically significant estimates showing a strong positive

[3]The full text of the decision can be found at http://www.cdcr.ca.gov/News/docs/USSC-Plata-opinion09-1233.pdf

relationship between crowding and violence, particularly among security level 2 populations.

It is a widely accepted doctrine among correctional practitioners, as well as philosophers on the topic, that crowding causes increased violence. Despite the research attention that has been paid to this topic, the empirical literature has thus far failed to present consistent evidence of such a relationship, providing null estimates as often as finding any positive correlation. A second contribution of this paper is descriptive evidence supporting a hypothesis that helps explain the puzzling disconnect between evidence and conventional wisdom. A summary of the hypothesis is that changes in the level of crowding in a prison are generally accompanied by changes to the composition of the population. This can confound estimates because compositional changes in individual propensities for violence are distinct from the direct effect of crowding that the researcher wishes to estimate. The presence of such a compositional effect is discussed in Section 4 and formally presented in a theoretical framework in Appendix A.

The results of the empirical estimation suggest that a ten percentage point decrease in the level of crowding (e.g. from 160% of capacity to 150% of capacity) is associated with an approximate 12% to 15% decrease in the rate of assault. To grasp the magnitude of this estimate consider that a 12% decrease in assaults for the entire state prison population would mean 85 fewer assaults *per month* in the state of California. In a more specific example, Avenal State Prison's total inmate population fell from $5,766$ to $4,946$ between September 2011 and September 2012, and the prison was designed for less than $3,000$ inmates. Thats about a 27 percentage point decrease in crowding, from 192% of capacity down to 165%. Avenal is a prison with a relatively low base rate of violence, approximately half of the statewide mean, yet this decrease in crowding would still be attributed a monthly decrease of 4.5 assaults.

This paper proceeds with the following structure. The next section provides background and context on the study of violence in contemporary prisons. A detailed history and description of California Public Safety Realignment is given in Section 3. Section 4 defines compositional effects and their implication for the literature and this research. Section 5 provides a description of the data that is used in this research and the challenges inherent to that data. Section 6 presents the two empirical strategies and the resulting estimates. A brief conclusion is presented in Section 7.

2 Prison Violence

Researchers have long sought to understand and predict the behavior of those who are incarcerated. As it stands, the body of literature studying inmate misconduct largely exists within the ambit of sociology, criminology, and psychology. This literature categorizes the determinants of misconduct into two groups, individual and institutional. Individual level covariates include both inherent characteristics – such as race, gender, and age – and historical characteristics – such as educational attainment and criminal record. Institution level covariates can include numerous environmental factors, a variety of security measures, and population density or "crowding".

A major challenge in evaluating the existing evidence in the field is inconsistency in the measurement of violence itself. Many studies use dependent variables that aggregate observations of violent misconduct with drug-related and other forms of non-violent misconduct (Goetting & Howsen, 1986; Ruback & Carr, 1993; Wooldredge, Griffin, & Pratt, 2001). This implies the restrictive assumption that the marginal effect of a covariate is stable across different types of misconduct, to which other research has shown contradictory evidence (Camp, Gaes, Langan, & Saylor, 2003; Steiner & Wooldredge, 2013). A 2013 paper by Steiner & Wooldredge presents the best available evidence on this issue, suggesting that there are significant differences in correlations of most covariates with the different types of misconduct. Accordingly, this paper narrows the focus to physical violence or the direct threat thereof, referred to in practice as *assault* and *battery*[4].

Understanding the primary determinants of violent behavior is foundational to improving management and enhancing safety within correctional institutions (DiIulio, 1990; Bottoms, 1999). This is true at every level of management and decision making in the correctional system, from the daily choices of correctional officers in the prison yard up to the strategic planning and policy decisions of wardens and legislators. Even the architectural design of correctional facilities has been associated with some forms of misconduct (Morris & Worrall, 2014).

We can hypothesize three relevant motivations for the study of prison violence, one a purely academic motive and the others policy oriented. The first, an academic desire to better understand violent behavior, would imply an interest in the causal effect of each potential covariate, individual or institutional, as well as any interactions between them. The second motive is to accurately iden-

[4]The legal definition of 'battery' is to cause bodily harm to another. The definition of 'assault' is the credible threat of bodily harm to another.

tify high-risk individuals, for which it is sufficient to simply identify correlations between individual characteristics and the likelihood of violent misconduct[5]. The last motive is to better assess the costs and benefits of policy and/or management options, which demands identification of the causal effect of institutional characteristics. To base such policy decisions on simple correlations, without consideration for causality, poses a risk of unexpected and potentially adverse outcomes. Hence in studying the relationship between crowding and violence, causality plays an important role in the value of the research.

This research aims to enhance existing evidence of a causal link between crowding and violent misconduct. Existing research often lacks any form of quasi-experiment or other source of exogeneity by which to make a claim for causality. Some studies estimate multivariate regressions, with cross-sectional or panel data, and show that crowding is associated with higher rates of violence (Megargee, 1977; Gaes & McGuire, 1985). Yet other research contradicts that conclusion, such as a 2003 study by Camp and several coauthors. Despite being one of very few studies that use individual inmate data, they do not find consistent evidence of a correlation between crowding and violence (Camp et al., 2003).

Of the research that does exploit some sort of quasi-experimental design, the exogeneity does not apply to the relationship between crowding and violence. Chen and Shapiro use regression discontinuity design to exploit the mechanism by which inmates are assigned to different security levels, granting "as good as random" variation with respect to security classification but not crowding (Chen & Shapiro, 2007). Another study has inmates with the same security classification randomly assigned to lower security level facilities and examines the implications for misconduct, but this random variation is also with respect to security level rather than crowding (Camp & Gaes, 2005). Additionally, Camp & Gaes point out that the correlation between crowding and violence is not statistically significant in their research design.

In recent theoretical research on the topic, Blevins, Listwan, Cullen, & Jonson (2010) propose a theory synthesizing the several disparate theories of what determines violent behavior in prisons. Blevins et al. acknowledge crowding as the most common "noxious stimuli" repeatedly linked to prison assaults and overall misconduct. The precept that crowding leads to increased violence is

[5] In identifying "high risk" inmates, there are notable social justice and equity concerns to be raised if individuals are ascribed differential treatment based on inherent characteristics. Discussion of these concerns is omitted since that motivation does not apply to this research.

also the prevailing view among practitioners in the field. However, these views seem at odds with the fact that empirical evidence of such a link is wholly unconvincing. This puzzle motivates the main objective of this research, to provide evidence of a causal effect of prison crowding on violent behavior, if such a link does in fact exist. It equally motivates the secondary objective of trying to understand why it is so challenging to identify a consistent relationship in the data.

3 California Public Safety Realignment

On May 23rd, 2011, the United States Supreme Court upheld a lower court ruling (Brown v. Plata) which had determined that the level of overcrowding in California prisons was so severe that the Eighth Amendment rights of prisoners were being systematically violated. The Court ordered California to reduce its prison population to 137.5% of design capacity on or before June 27th, 2013. Given the prison population at the time of this order, the required reduction amounted to approximately one quarter of the existing California prison population. According to the California Department of Corrections and Rehabilitation (hereafter CDCR) population reports[6] the total prison population in California in January 2011 was over 156,000. This number fell to 135,000 in January 2012, and further to 124,000 in January 2013. Although CDCR did not quite achieve the full reduction demanded by the courts[7], the total prison population declined more swiftly and significantly than any large US prison population has in recent history.

Because the law that resulted from the court mandate was strict sentencing reform, it is important to first understand the process by which individuals enter the California prison system. There are two possible channels by which a new admit is referred to a California prison – either through the courts following conviction or through the parole system for violation of the parolee's conditions of parole. In either case, the new inmate is first sent to one of the select prisons known as reception centers, of which there were nine in 2011. Inmates are typically held for several months at the reception center awaiting a classification hearing. This hearing determines which security classification the inmate should be assigned to, after which the same committee selects a suitable

[6] Available at http://www.cdcr.ca.gov/Reports_Research/Offender_Information_Services_Branch/Population_Reports.html

[7] The target reduction was later achieved after the implementation of Proposition 47, which changed sentences for a set of minor drug and theft offenses from felony to misdemeanor

prison for the inmate to serve the remainder of their sentence. The inmate is then transferred to the assigned prison, where they are housed with inmates of the same security classification.

Within a prison, prisoners of one security classification do not generally interact with prisoners of other security classifications. Each California prison has several different facilities within it and these are designed to operate independent of one another. Thus a prisoner that is classified as security level 2 will be held in a level 2 facility, which is completely separate from the housing and recreational areas of other security levels. Reception center populations and special needs populations[8] are also held in separate facilities. This segregation within prisons creates the possibility for greater levels of crowding in some areas than in others.

AB 109

California achieved the massive reduction in population mentioned above by introducing Assembly Bill 109 (AB 109) and signing it into law. The new law took effect on October 1st, 2011, making two major changes to how inmates are handled in California. First, technical parole violators who were previously taken back into state custody are thereafter sent to county jails, with a few exceptions for very serious violent and sexual offenders. This is a shift from the aforementioned practice wherein such parole violators were remitted to a nearby state prison for a term of up to twelve months. The second major element of the reform defined a set of non-violent, non-sexual, non-serious felony offenses for which the sentences were to be served in county jails rather than state prisons.

AB 109 did not commute any existing sentences and no prisoners held in state prison prior to implementation of the law were transferred to county jails; the law only changed who would take custody of new admissions. Despite the intervention being a change in flow rather than stock, the impact on the prison population was rapid and distinct. This is depicted in Figure 1. Essentially, California prisons had a high rate of "churn" in their populations and the new law caused a sharp decrease at the front end of that churn without immediately affecting the back end. Hence the true nature of the shock is that the "vacancies" left by released prisoners are no longer being filled at the same rate as they were prior to the new law.

Note that the shock created by AB 109 was selective by nature, designed to target non-violent

[8] "Special needs" in the CDCR is what would commonly be known as protective custody.

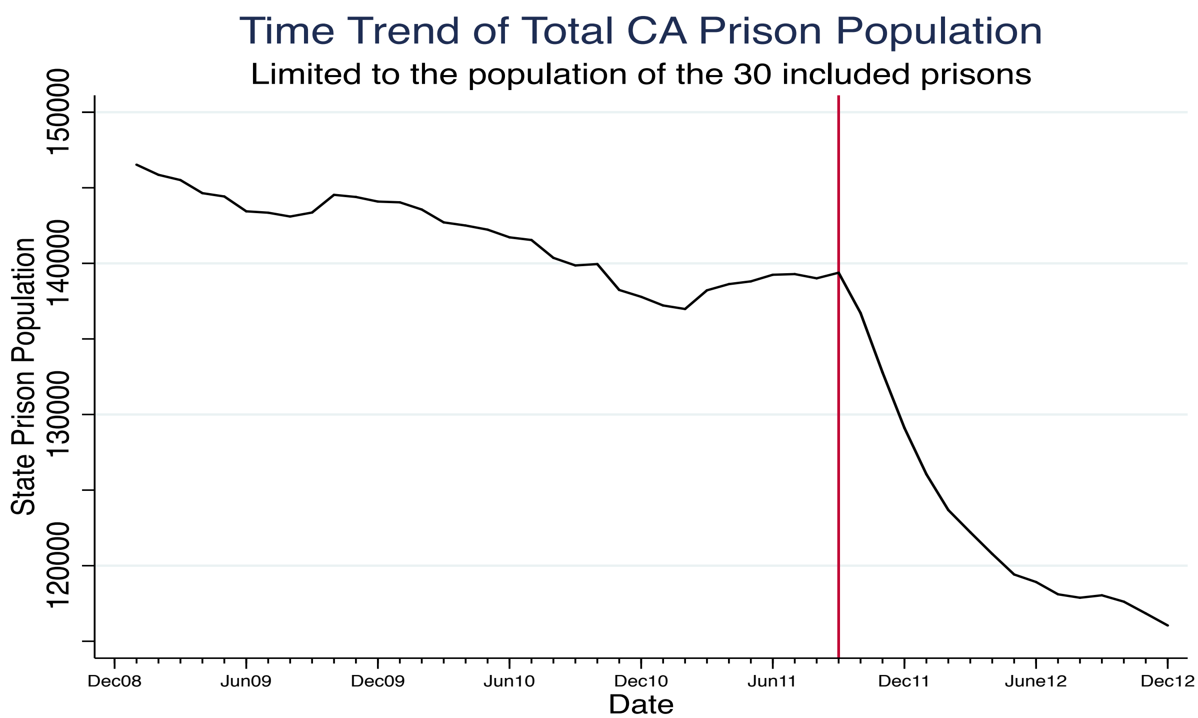

Figure 1: *Total population of male prisoners incarcerated in the state of California, observed monthly. The vertical line denotes the last observation prior to implementation of AB 109.*

offenders[9] for diversion. The population decrease can therefore be expected to concentrate among two subpopulations. The first, rather obvious given that they handle all new admissions, is the entirety of the shock is channeled through the relatively few reception center facilities in the state. Parole violations made up a significant proportion of admissions prior to AB 109, so the dramatic impact on reception centers was predictable. After passing through reception centers the residual impact is concentrated among security level 2 populations. This is because the point system by which inmates are assigned a security classification makes it unlikely to begin at the lowest classification (level 1) and also unlikely that any inmate will accumulate enough points for level 3 unless they have a long criminal record or are convicted of a very serious felony. Given that the law targets lower level felonies, it follows that we should expect to see the secondary effects focused among the security level 2 populations of California prisons. Rather than a liability, this selective compositional feature of the shock provides a measure of variation that is important to the empirical strategies that follow. This will be discussed further in the data and empirical sections.

Figures 2 and 3 show the time trends of the different subpopulations for the entire state. It is apparent that the largest decreases are indeed among the reception and security level 2 populations depicted in figure 2. More specifically, the effect on the reception center populations is immediate, very sharp, and appears to stabilize again rather quickly. The shock to the level 2 population lags by one month, not surprisingly, then there is a sharp decline and it takes longer (into the eighth or ninth month) to stabilize at what appears to be a new equilibrium. Figure 3 clearly demonstrates that the trends of each of the other subpopulations are not sensitive to the implementation of the new law. In total, averaging over the six months prior to implementation and the first six months of 2012, the reception center population falls by about 45% and the Level II population falls by a more modest 12%. There are also some moderate decreases in other subpopulations, but none exceed 6% and these can just as likely be attributed to long term downward trends.

Reception Adjustment

As mentioned previously, it was not unexpected that AB 109 would greatly reduce reception center populations. All else constant, this would have resulted in prisons with reception facilities that

[9] Parole violators may or may not have been originally convicted of a violent offense, however Orrick & Morris (2015) show that technical parole violators are significantly less likely to engage in misconduct that inmates admitted to prison for new offenses

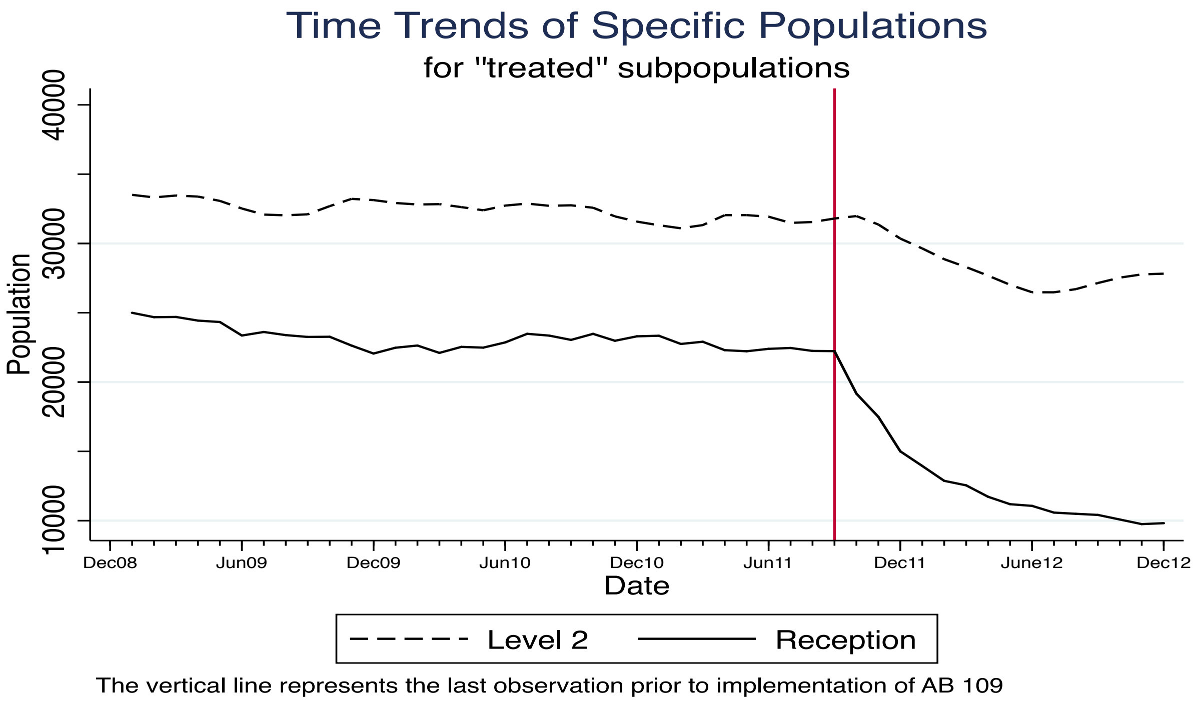

Figure 2: *This figure shows the trends for the two subpopulations among which the shock from AB 109 was concentrated, summed across all 30 California prisons included in this study. The vertical line denotes the last observation prior to implementation of AB 109.*

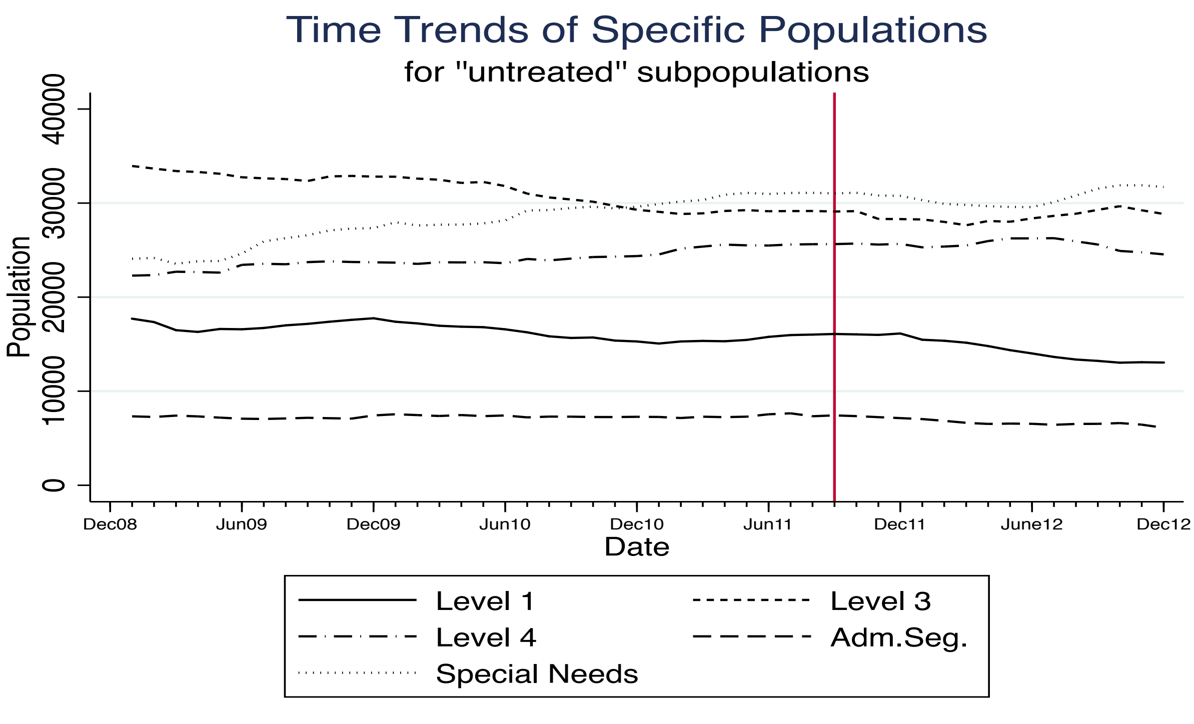

Figure 3: *This figure shows the trends for the major subpopulations which were less impacted by AB 109, summed across all 30 California prisons included in this study. The vertical line denotes the last observation prior to implementation of AB 109.*

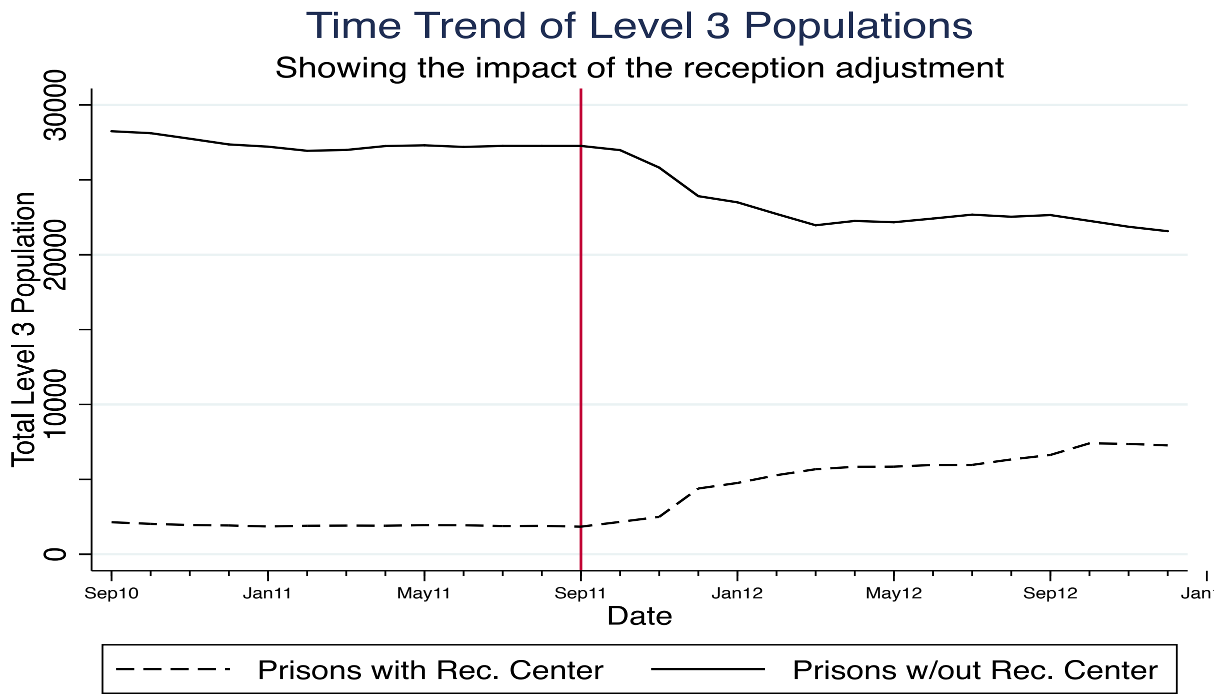

Figure 4: *This figure shows the impact of the reception adjustment that followed implementation of AB 109. The time trends are for sum of security level 3 populations parsed by whether the prison has a reception center facility or not. The vertical line denotes the last observation prior to implementation of AB 109.*

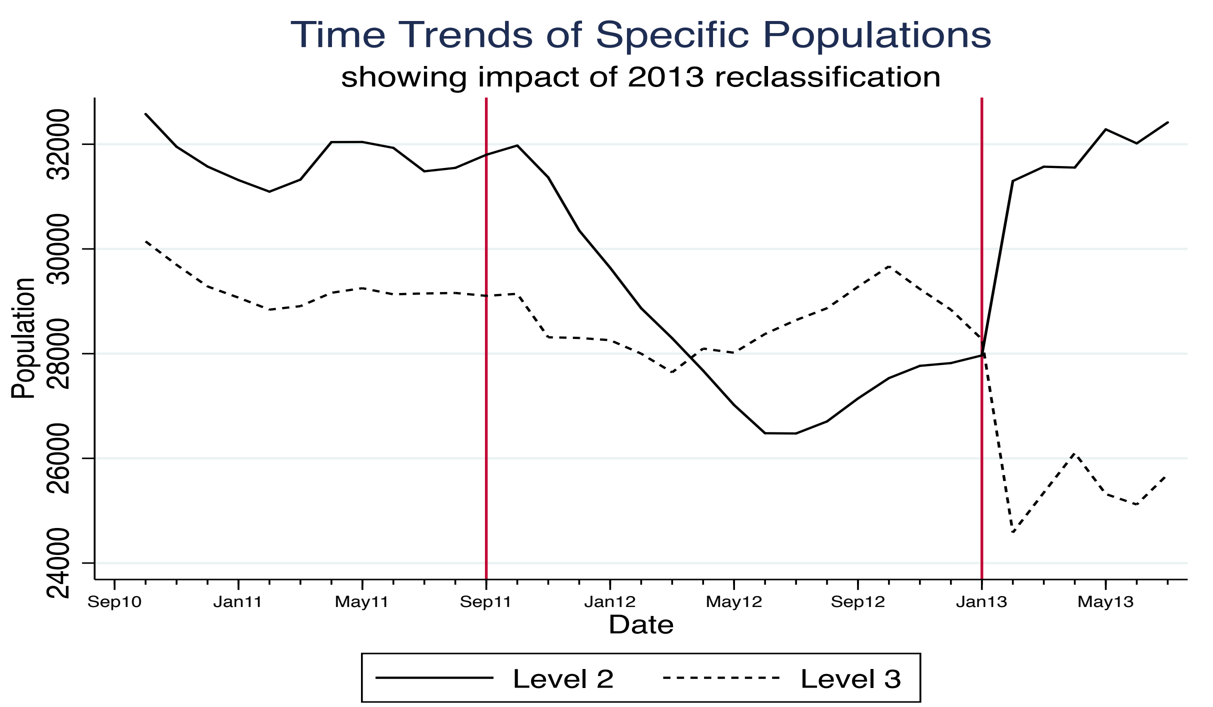

Figure 5: *This figure shows level 2 and level 3 population trends through implementation of both AB 109 and the new classification system. The vertical lines denote the last observation prior to implementation of AB 109 and January 2013.*

were suddenly near or below their design capacity while other facilities, both at other prisons and within the same prison, remained severely overcrowded. The Reception Adjustment[10] (hereafter RA) was a reclassification of certain reception facilities to serve an alternate subpopulation. This did not mean that any given prison was no longer a reception center. Each California prison has between three and nine individually defined facilities within its organizational structure and most reception centers had two or three of these dedicated to reception populations. So when RA occurs reception population are simply consolidated into fewer facilities.

RA complicates the impact of AB 109 in two ways. First, it makes the decrease in actual crowding for reception center populations less dramatic than implied by the population reduction. Although the statewide reception population is approximately halved by AB 109, to a smaller degree RA also decreases the design capacity dedicated to that population. Therefore RA diminishes the degree of the AB 109 shock to crowding in reception populations. Simultaneously, it decreases crowding for some other population by increasing the total design capacity devoted to them in the state. In nearly every case the repurposed facilities were filled with level 3 inmates. Although some of the new inmates were likely transferred from within the same prison, the overall transfers were statewide[11]. So while AB 109 does not significantly decrease the statewide level 3 population, evidenced in Figure 3, it does result in decreased levels of crowding for that population.

The evidence of decreased crowding for level 3 populations is given in Figure 4. Looking only at the number of level 3 inmates in reception centers, the dashed line shows that there were very few prior to AB 109 and that number begins to climb shortly after implementation of the law. On the other hand, the total level 3 population in all other facilities, the solid line, decreases in near perfect synchronicity with the increases at reception centers. The total decrease in non-reception center level 3 population is of a magnitude similar to the overall impact of AB 109 on the statewide level 2 population. Similar figures are provided in Appendix B for each of the other subpopulations, showing that none have a distinct shift like the one seen here for the level 3 population.

[10]"Reception Adjustment" is the author's term and does not represent official CDCR language.
[11]Many reception centers did not have any level 3 population prior to this.

Reclassification

This time period of the following analysis is truncated prior to January 2013 because of another policy adjustment that was implemented around that time. Likely in response to the statewide decrease in level 2 inmates following AB 109, the CDCR commissioned a review of their classification system. This review and the resulting adjustment in the classification system changed the point thresholds for certain security classifications. These changes led to a shift of inmates from level 3 classification to level 2 classification. Figure 5 shows the time trends of statewide level 2 and level 3 populations into 2013 and the impact of this policy change is very evident. It is not clear in the available data what portion of these inmates were transferred between facilities or if some facilities were repurposed (similar to the RA repurposing) to accommodate the greater number of level 2 inmates.

Although this second policy shock provides opportunity to explore some interesting research questions about composition and crowding, the variation is quite different from the that induced by the AB 109 shock. As such the current research is limited to the months preceding the reclassification.

4 Compositional Change: A Theoretical and Empirical Oversight

In any conception of the sequence of events that leads to a violent assault, individually rational behavior requires that the decisions of each participant be informed by the characteristics and choices of the other involved parties. As the saying goes, it takes two to "tango". Given any degree of heterogeneity among inmates, this implies that changes in the composition of a prison's population can influence the rate of violence in that prison. Since any change to the level of crowding is likely to be accompanied by a change in the composition of the prison population[12], it is a potentially critical oversight to not consider the effect of compositional change in any study of prison crowding and violence.

[12] Increasing or decreasing crowding is most often done by increasing or decreasing the population size, which can be expected to change the composition of the population unless the selection by which changes are made is as good as random. Such policy or administrative changes tend to be distinctly non-random, as in the case of AB 109 which specifically targeted non-violent criminals.

This section provides a description of three simultaneous channels, or mechanisms, by which prison crowdedness may effect the rate of violence in a prison and then summarizes the implications for this paper and other empirical work in this area. The three mechanisms represent broad conceptual channels meant to capture all the reasonable means by which crowding may be correlated with violent behavior. Appendix A develops a model that formalizes the three mechanisms and presents relevant derivations.

1. ***Structural Mechanism:*** Increased crowding leads to increasingly limited personal space and more individuals sharing a fixed set of available resources – such as basketball courts, payphones, and restroom facilities – which in turn leads to a higher frequency of potentially contentious encounters between inmates. Therefore increased crowding can cause each individual to experience a greater number of potentially violent confrontations with other inmates in a given time period. This mechanism is likely to be reflected by a positive association between crowding and violence.

2. ***Behavioral Mechanism:*** Crowding exacerbates the individual's lack of access to personal freedoms, amenities, and basic necessities, potentially leading to a behavioral increase in an individual's willingness to resort to violent behavior. This, in turn, increases the likelihood that any given contentious interaction between inmates becomes violent[13]. Sleep is a classic example of a basic human need whose deprivation has been shown to increase aggressive behavior (Kamphuis et al., 2012). This mechanism is also likely to be reflected by a positive association between crowding and violence.

3. ***Compositional Mechanism:*** The manner in which a particular change in the level of crowding changes the composition of the inmate population, especially with respect to individual propensities for violent behavior. Depending on the specific policy design, this can result in a population that is either more or less prone to violent behavior, on average. This mechanism could therefore result in either a positive or negative association between crowding and violence.

[13]This mechanism may be viewed as an emotional response wherein the individual becomes more irritable or unstable, or as a rational response where the individual recognizes a lower opportunity cost associated with violent behavior. The rational response assumes that violent behavior results in punishment with some positive probability and the opportunity cost is then the expected utility of avoiding the implied sanctions. That expected utility is reduced if prison life without sanctions grants access to fewer resources or less freedom due to crowding.

The first two mechanisms can be thought of as "pure" crowding mechanisms, representing direct effects of crowding itself. The compositional mechanism is distinct in that it occurs as a result of correlation between changes in crowding and population composition, where the actual impact on the rate of violence is derived from the compositional change rather than the change in crowding. In addition, the nature of compositional change, and thus the resulting effect of the compositional mechanism on violence, is dependent upon the case specific process of selection by which the population is increased or decreased.

In the case of AB 109, as well as nearly any other policy intervention meant to decrease crowding, the new law decreases crowding by reducing the portion of the population least likely to be prone to violent behavior. After implementation of the law, offenders convicted of non-violent, non-serious, and non-sexual felonies are no longer sentenced to serve time in state prisons; this effectively redirected many of the least violent new admissions away from California prisons[14]. Thus the resulting distribution prisoners is expected to be more prone to violent behavior, on average. So while the structural and behavioral mechanisms may decrease the rate of violence after AB 109, the compositional mechanism is expected to do the opposite, increasing the rate of violence.

The three mechanisms can be conceptually contrasted with the example of a prisoner using the payphone in the prison yard. Consider a relatively well behaved inmate, Richard, at a maximum security prison who calls his mother from the prison payphone every Sunday. AB 109 takes effect and the prison population decreases. As the prison becomes less crowded, it becomes less likely that another inmate will seek to use the phone while Richard is using it, harassing him to cut his call short. This is an example of the structural mechanism since such an interaction could have resulted in violence. At the same time, Richard gets more sleep now that the prison has reverted from triple to double occupancy in each cell. He is therefore marginally more patient and less prone to losing his temper. This constitutes an element of the behavioral mechanism. On the other hand, the diminished population in the prison is due to fewer non-violent offenders who are less likely to resort to violence than certain other types of offenders. As a result when Richard is harassed it is more likely to be by an inmate who is aggressive and prone to violence than prior to AB 109. This is the effect of the compositional mechanism.

[14] Research shows that violent crime and past criminal records are strong predictors of future violent misconduct (Walters & Crawford, 2013).

The implications of these mechanisms for the empirical study presented in this paper can be understood through Equation 1. The elasticities in this equation are derived from an identity (Equation 5 in the appendix) stating that the total violence in a prison will equal the average probability that any pairwise interaction results in violence multiplied by the total number of such contentious interactions in the prison per unit time. The full model and derivation is available in Appendix A.

The term on the left side of Equation 1 is the elasticity of aggregate violence, V, with respect to a policy shift parameter, λ. The shift parameter is defined such that prison crowding, c, exhibits unit elasticity with respect to it (a policy that *decreases* crowding by 10% is represented by a 10% decrease in λ). The first term on the right side of the equation is the elasticity of violence with respect to crowding. This term encompasses both of the "pure" crowding mechanisms from above – structural and behavioral – and represents the impact of crowding that researchers typically seek to estimate. Yet, without any direct measurement of compositional changes, the latter elasticity is inevitably confounded with the "compositional elasticity" represented by the final term in the equation. This last elasticity measures how the probability of any particular encounter becoming violent, π, responds to the policy represented by λ. $E_{\pi:\lambda} < 0$ implies that as the policy increases crowding the population becomes less prone to violence or conversely if the policy is decreasing crowding ($\Delta\lambda < 0$) then the remaining population, on average, becomes more prone to violence. As explained previously, the latter is exactly what is expected in the case of AB 109.

Derived Elasticity of Aggregate Prison Violence

$$E_{V:\lambda} = E_{V:c} + E_{\pi:\lambda} \tag{1}$$

Equation 1 provides a mathematical representation of what is proposed in the earlier description of the mechanisms. Assuming there is some validity to the structural or behavioral mechanisms, it is the case that $E_{V:c} > 1$ and therefore the rate of violence increases with the level of crowding. However, when empirical estimates actually represent $E_{V:\lambda}$ then the desired $E_{V:c}$ is conflated with $E_{\pi:\lambda}$. Although the sign of $E_{\pi:\lambda}$ depends on policy design, there are many cases where the obvious expectation is $E_{\pi:\lambda} < 0$ and this implies a downward bias in estimates meant to capture the $E_{V:c}$ relationship.

Unfortunately, California prison data on individual inmate misconduct is not currently available. Nor is there data measuring capacity or rates of misconduct for the individual facilities within each prison. This means that it is not feasible with existing data to separately identify the two crowding mechanisms of this model nor to precisely isolate the compositional mechanism. Therefore the empirical strategies used in this paper do not attempt to directly identify the compositional effect of AB 109. Instead, because the AB 109 population shock is concentrated among three distinct subpopulations and at least two of those interact in predictably different ways with the compositional element of the policy, the potential for a compositional effect is used to analyze between-group differences in the point estimates. Reflectively, the differences in point estimates can also be taken as supportive evidence of an existing compositional mechanism. In addition, the potential presence of the compositional mechanism contributes the implication that the estimated coefficients are in fact lower bounds on what would be considered the true effect of crowding on violence.

5 CompStat Data

Panel data used for this research has been taken from the California Department of Corrections and Rehabilitation (CDCR) CompStat Reports. These contain monthly observations for each adult correctional facility in the state of California. There are 35 currently operational prisons in California, five of which are excluded from the analysis. The excluded prisons are either medical facilities, female detention centers, or were not operational at the time of the policy shock. The time period of analysis is limited to July 2008 through December 2012, due to irregularities in the earlier data and the January 2013 reclassification that was discussed in section 3. Given that AB 109 was implemented at the beginning of October 2011, the data in use spans three years prior to and fifteen months post implementation of the law.

The variable of interest is the level of overcrowding in each prison, which is constructed in this analysis from two variables in the CompStat data. *Total population* is a simple count of the total number of inmates held in a prison in a given month. *Design beds* is reportedly the number of beds that a given facility was designed to hold. The institutional definition of *design beds* for a facility is a single bunk per cell and single level bunks in dorm housing[15]. However, there is minor month-to-month variation in the CompStat measure of *design beds*. This variation is not consistent with the idea that prisons have a fixed capacity – notwithstanding new construction or demolition, which would not be characterized by such frequent and minor changes. Therefore *design beds* for each prison is averaged over the six months preceding implementation of AB 109 and this is taken as the *fixed design capacity* of each prison. Table 1 shows that these two measure of capacity are quite similar, *fixed design capacity* having only slightly less variation. Prison crowding ($crowd_{it}$) is defined in this research as the ratio of *total population* to *fixed design capacity*[16].

The CompStat data includes a number of measures of misconduct, broadly defined as either disciplinaries or incidents. Disciplinaries are individual reports of misconduct for each prisoner, which are included in their personal files. There are several different types of disciplinary, ranging from simple conduct or cell phone possession to assault and battery or murder. Incidents are recorded in slightly more detail (such as the type of drug confiscated) but with less frequency, suggesting that a disciplinary can be issued without having to write up a full incident report or that each incident may involve an unspecified number of individuals.

The dependent variable used for this research is the monthly sum of disciplinary reports for assault on an inmate, assault on staff, battery on an inmate, and battery on staff[17]. The inclusion of murder and attempted murder in this sum does not noticeably impact the estimates reported below, which is expected since such attacks are relatively infrequent. Although assault and battery are measured separately in the more recent CompStat reports, they were not in the earlier years and are therefore summed into a single variable, *assaults*, in the statistics below.

In Table 1 assault statistics are given for all assaults and then broken down by whether the victim was a staff member or an inmate. Assaults on inmates are the most frequent, averaging more than 18 per month in each prison; however, at just below 5 per month, assaults on staff members are also quite common. The other categories of violent misconduct occur with less frequency and

[15]This definition of capacity could be seen as reasonably conservative, which may explain why the target given in the court mandate was for the CDCR to reduce overcrowding to only 137.5% of design capacity.

[16]This measure of prison crowding differs slightly from the official measures used by the CDCR, likely due to the manner in which *fixed design capacity* is constructed. The measure defined here does closely track the official measure and has been determined to be the most appropriate for this research given the timing of the policy shock being studied.

[17]As defined previously, the legal distinction between an assault and a battery comes down to the credible threat of bodily harm versus actually causing bodily harm.

Table 1: Simple Summary Statistics

	count	mean	sd	min	max
Measures of Violence					
Rate of Assaults	1620	.537083	.3496848	0	2.777778
Total Assaults	1620	23.45247	14.4966	0	133
Assaults on Inmates	1620	18.72531	12.75872	0	126
Assaults on Staff	1620	4.72716	4.829611	0	58
Murders and Attempts	1620	.5197531	2.433345	0	67
Rioters	900	10.43556	28.4308	0	466
Resisting Staff	900	3.455556	5.287425	0	49
Posessions of a Weapon	899	5.292547	5.950058	0	46
Population & Crowding					
Crowding (P/K)	1620	1.872671	.2652445	1.155107	2.44784
Total Population (P)	1620	4566.968	1084.344	2212	7179
Design Beds	1620	2451.812	612.4285	1234	3880
Fixed Design Capacity (K)	1620	2466.111	608.9742	1557	3789.333
Population Shares					
Security Level 1	1620	.1094138	.1547788	0	.685277
Security Level 2	1620	.2131347	.2962029	0	.9995067
Security Level 3	1620	.2329096	.2615549	0	.9088176
Security Level 4	1620	.1967216	.2658214	0	.8865633
Reception Center	1620	.1383862	.2605312	0	.9434235
Special Needs	1620	.2042753	.2238708	0	.9279493
Admin. Segregation	1620	.0543071	.0263553	0	.1202622
ADA Inmates	1620	.0637266	.0553348	.0031173	.4041008
CCCMS Inmates	1620	.1969473	.1090689	0	.4756164
Single Inmate Cells	1620	.0473859	.0853995	0	.4496124
Program Enrollment					
Prison Industries	1620	148.5117	162.1272	0	616
Academic	1620	413.923	306.4613	0	1687
Non-PIA Work	1620	2251.761	1171.362	0	5591
Subst. Abuse	1620	103.7352	229.5731	0	1818
Subst. Abuse Waitlist	1620	56.23951	103.6996	0	603
Observations	1620				

The dependent and key explanatory variables are indicated in italics.

most were not reported in the early years of CompStat, which is noticeable in Table 1 by the fewer numbers of observations for these types of misconduct. Assaults were selected as the most appropriate category of violence for this study because, in addition to being a reasonable area in which to expect responsiveness to crowded conditions, their high frequency indicates they are the most present threat to the safety of inmates and staff. Further, assaults are a distinct and well-defined form of misconduct, making their measure less susceptible to misreporting by the prison staff.

The data also include population counts for each of several subpopulations, which are used to generate population shares of each. There are six major subpopulations: the four levels of security classification, special needs, and reception center populations. Each of these populations reside in separate facilities. Administrative segregation units constitute an additional type of facility, but these are smaller and serve a more temporary purpose. The security classifications are ranked in ascending level of security threat, one to four. Security level one prisoners are eligible for housing units that are not within the prison fences and are also permitted to have jobs in the prison that allow them relatively free movement within the facilities. Security level two and three require much closer supervision and are not permitted to be outside secure areas, the major difference between the two levels typically being dormitory housing vs. cells. Security level 4 is reserved for the most disruptive and violent prisoners, although a sufficiently heinous crime can result in this classification without any record of institutional misconduct. The special needs and administrative segregation populations are held apart from the rest, each for their own reasons; one for long-term protective custody and the other a temporary punitive or safety measure, respectively. There are several other subpopulations that are not housed exclusively, such as ADA (Americans with Disabilities) inmates, single-cell inmates, and the CCCMS (Correctional Clinical Case Management Services) population. The shares of these are included as controls in the empirical strategies. Finally, the CompStat data includes counts of inmates with life sentences with and without possibility of parole. Unfortunately, there is a significant amount of missing data for these two variables so they have been excluded from the analyses.

All of these data are observed at the prison level. However, AB 109 affects crowding, and thus misconduct, at the facility level. Therefore observed rates of assault are averages across the facilities within a prison, which makes the population shares of each subpopulation both necessary to the identification strategy and critical as direct controls for the effect of changing shares. The latter is due to an observable element of compositional change that occurs across the whole prison. Suppose a prison has a level 2 facility and a level 4 facility, each of equal capacity and population size. The AB 109 shock reduces the the level 2 population but not the level 4 population. Then, above and beyond any differences because of reduced crowding, the rate of violence in this prison will have increased due to the fact that the population of the level 4 facility makes up a greater share of the total population and level 4 facilities have much higher rates of violence, on average, than level 2 facilities. Thus without controlling for population shares, the implementation of AB 109 would be correlated with changes in rates of violence that were not due to the effect of diminished crowding.

There are no demographic controls available in these data (such as age and race statistics for the prison population) but there is fairly detailed information on program participation in academic, vocational, work, and drug rehabilitation programs. Tables 1 and 2 include variables for the degree of enrollment in these programs. Prison Industries (PIA) is a work program that produces marketable products, with higher skill positions that pay relatively high wages. Non-PIA work positions are the more common prison positions such as maintenance and food service. Each of these variables is a simple count of enrollment, except for the substance abuse program for which both enrollment and waitlist are included.

Table 2 breaks the summary statistics into two periods, pre and post implementation of AB 109. There was a slight downward trend in total population over the full time period, so the difference in the population means reported in the table slightly exaggerates the actual policy impact on population and crowding. Table 2 illustrates that there were moderate decreases in all measures of assault and objectively larger decreases in *total population* and *crowding.* One notable point in this table is the decrease in *design beds*, minor though it is. This decrease implies that if one believes *design beds* to be a more appropriate measure of capacity than the fixed measure used in this research, then *crowding* as currently defined actually exaggerates the true impact of AB 109 on California prison crowding. Exaggerating the impact on crowding in this way is of little concern since it would only result in attenuation bias, which means the estimated coefficients are smaller and less significant than they would be otherwise.

Table 2 also highlights the dramatic decrease in reception center populations following AB 109. Excessive focus on this impact to reception populations is discouraged, since the effect on crowding

Table 2: Pre and Post Statistics

	Pre	Post
Measures of Violence		
Rate of Assaults	0.55	0.50
	(0.35)	(0.36)
Total Assaults	25.00	19.43
	(14.62)	(13.36)
Assaults on Inmates	19.95	15.53
	(12.91)	(11.78)
Assaults on Staff	5.05	3.90
	(4.83)	(4.74)
Population & Crowding		
Crowding (P/K)	1.95	1.67
	(0.24)	(0.20)
Total Population (P)	4755.79	4076.02
	(1070.81)	(959.11)
Design Beds	2480.08	2378.33
	(613.68)	(603.67)
Subpopulations		
Level 1	556.89	481.57
	(846.82)	(821.05)
Level 2	1090.50	944.70
	(1537.78)	(1332.32)
Level 3	1059.96	952.60
	(1180.91)	(938.93)
Level 4	792.95	852.42
	(1076.58)	(1109.62)
Reception	778.33	413.69
	(1403.34)	(1017.92)
Special Needs	915.41	1021.08
	(1033.05)	(1039.39)
Program Enrollment		
Prison Industries	154.38	133.25
	(165.36)	(152.53)
Academic	436.19	356.03
	(334.99)	(204.55)
Non-PIA Work	2344.31	2011.14
	(1219.25)	(998.36)
Subst. Abuse	128.54	39.24
	(263.25)	(61.89)
Subst. Abuse Waitlist	51.91	67.62
	(94.22)	(124.48)
Observations	1170	450

Means reported. Standard deviations are in parenthesis.

was significantly countered by the reception adjustment. An extrapolation based on the observed decrease in reception populations and increase in level 3 populations at reception centers suggests the true decrease in crowding at reception facilities was approximately 40 percentage points, only slightly greater that the decrease at level 2 facilities. This approximation is further supported by the population means presented by Table 4 in the next section.

6 Empirical Strategies and Results

The simplest and most common approach to estimating the effect of a policy shock such as AB 109 is a difference-in-differences (DD) strategy. This section begins with a DD approach and then develops a more sophisticated instrumental variables (IV) identification strategy. The IV strategy builds on the same source of variation as the DD strategy by better capturing the varying time intensity of treatment across the treated populations. The dependent variable, Y_{it}, in both the DD and IV strategies is the natural log of the rate of assaults in prison i during month t[18]. Results in Appendix B show there is no meaningful change when the dependent variable is altered to include other violence, such as murder and attempted murder, or to exclude assaults and batteries on staff members. The log-linear form[19] is an intuitive way of incorporating the expectation of a nonlinear relationship between crowding and violence. Such expected nonlinearities are a natural conclusion of the frequent conjecture that "violence begets violence".

The log-linear form, with the $crowd_{it}$ variable constructed as it is, makes the coefficients reported below semi-elasticities. These are interpreted as the *percent* change in the rate of assaults associated with a *percentage point* change in crowding. For example, the 0.6 point estimate in column 3 of Table 3 asserts that a *ten percentage point* increase in crowding is associated with a *six percent* increase in the rate of assaults. The percentage point changes in crowding are with respect to the percent by which the population exceeds the prison's design capacity.

Table 3 provides estimates from a basic ordinary least squares model with prison fixed effects. These estimates give an idea of the baseline correlation between crowding and violence in these data, absent the quasi-experimental design used in later estimates. The model is estimated using

[18]Rates of violence in this literature are measured per 100 inmates.

[19]The log-linear form the transforms the dependent variable so that marginal changes are approximations of the percent change in the original variable. Thus a 0.1 increase in $ln(Y_{it})$ is and approximate 10% increase in Y_{it}.

Table 3: OLS Regression with Prison Fixed Effects

Dependent Variable: Log Rate of Assaults

VARIABLES	(1) Trend	(2) TimeFE	(3) Trend	(4) TimeFE
Crowding (P/K)	0.624*	0.483	0.601	0.621
	(0.306)	(0.342)	(0.443)	(0.470)
Security Level 2	-1.527*	-1.724**	-0.0466	-0.0920
	(0.784)	(0.776)	(1.112)	(1.137)
Security Level 3	-0.0361	-0.329	0.119	0.103
	(1.021)	(0.989)	(1.247)	(1.235)
Security Level 4	-0.101	-0.442	0.113	0.0402
	(1.262)	(1.218)	(1.296)	(1.263)
Reception Center	-0.131	-0.377	0.338	0.168
	(0.797)	(0.792)	(0.926)	(0.927)
Observations	1,440	1,440	1,140	1,140
Controls	X	X	X	X
Period	Full	Full	Pre-AB109	Pre-AB109

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

a flexible time trend or time fixed effects and the final two columns restrict the time period to only include observations prior to implementation of AB 109. The coefficients on crowding are only marginally significant if at all and suggest a semi-elasticity of approximately $0.5 - 0.6$. The weak statistical significance of these correlations is consistent with the overall state of existing empirical evidence on this topic, as discussed in Section 2.

The coefficients for the shares of major subpopulations are also reported in Table 3. These coefficients preview the importance of the share of security level 2 population and its dependence upon the variation that occurs as a result of AB 109. Note that because the shares of these subpopulations are generally very stable over time, most of the correlation between assaults and each share is absorbed by the prison fixed effect. Table 9 in Appendix B shows the raw correlations between each population share and the rate of assaults. The coefficients in Table 3, on the other hand, pick up the effects, or lack thereof, of time variation in the shares. However, AB 109 is responsible for the bulk of such variation and, among the treated populations, the effect of this is only apparent in the level 2 coefficient. Furthermore, even the effect for level 2 share dissipates

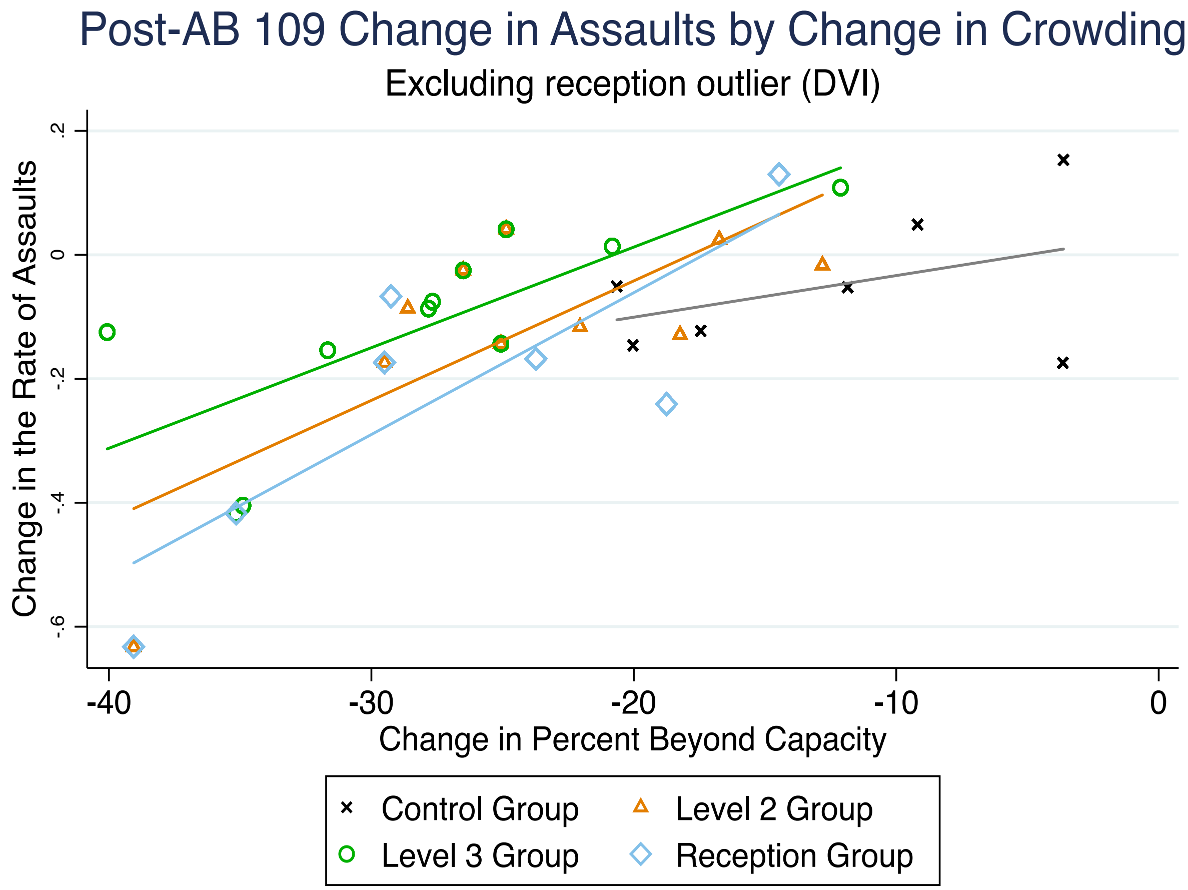

Figure 6: *This figure shows the correlations between change in crowding and the change in the rate of assault following implementation of AB 109, separated by "treatment groups". Changes are calculated between the 6 month average just prior to AB 109 (Apr11 – Sep11) and first half of 2012 (Jan12 – Jun12). The outlier observation for Deuel Vocational Institute (a member of the reception group) has been omitted from this figure.*

entirely in columns 3 and 4 when the months following AB 109 are excluded from the regressions. This suggests that implementation of AB 109 is the source of the only significant variation in the rate of assaults that is correlated with changing population shares.

Figure 6 emphasizes the importance of the the treated subpopulations in identifying the impacts of AB 109. The figure depicts the policy induced variation that is exploited by the empirical strategies in the remainder of this section, the change in prison crowding and the change in the rate of assault. For the figure, these changes are calculated as the average in the six months preceding AB 109 differenced from the average in the 4th through 9th months following AB 109. The prison groupings depicted are defined as any prison whose total population is made up of at least 20% of the given subtype and the control group is the set of prisons that have less than 20% share of each of the treated subpopulations. Note that these groups are not mutually exclusive. Also, there is one observation point excluded from Figure 6. One prison in the reception group is such a outlier that it radically distorts the fitted line for that group. That prison was excluded from the figure for presentational purposes. However, an otherwise identical figure with the outlier included is shown in Section 6.3 with a brief discussion of the issue.

What Figure 6 illustrates is the overall impact of AB 109 on crowding and associated changes in violence in relation to the treated subpopulations. Reductions in crowding are much greater for all of the treatment groups relative to the control group and those reductions are clearly associated with reduced violence. In addition, the gradient by which violence changes is notably steeper for the treatment groups than for the control group.

6.1 Difference-in-Differences Strategy (DD)

$$Y_{it} = \beta_0 Post_t + \beta_1 Post_t * Treat_i + \beta_2 X_{it} + \delta_i + \epsilon_{it} \tag{2}$$

The concept of the difference-in-differences (DD) strategy in this setting is for a subset of prisons to be "treated" with an exogenous shock that reduces the degree of crowding in those prisons, while other prisons remain untreated. In such a case, differencing the post-shock change in violent behavior for the treated prisons with that of the untreated prisons provides an unbiased estimate of the causal effect of crowding on violence. The reality of the quasi-experiment provided by AB 109 deviates from such a straightforward DD setting in two important ways. First, there are three different subpopulations for which crowding is significantly decreased by AB 109. Each of these subpopulations experience a different degree or form of treatment and therefore must be accounted for as three simultaneous but distinct treatments. Second, the unit of observation in the data, a prison, is not the same as the treatment unit, a facility. This means that each observational unit is subject to partial treatment by each of the three treatment types, although no one prison has a large proportion ($> 5\%$) of more than two treated populations.

The basic form of the DD estimation is represented in equation 2. The variable $Post_t$ is an indicator for whether the observation is post-implementation of AB 109. $Treat_i$ is a vector of variables for the three treatment groups, Reception, Level 2, and Level 3; each is equal to the share of prison i's total population that is of the given type, averaged over the six months immediately preceding implementation of AB 109. X_{it} is a vector of control variables, which at a minimum includes indicators for when the reception adjustment occurs at a given reception center. In the full set of controls (used for most specifications and indicated in the tables by an X in the row labeled *controls*) are all variables from Table 1 listed under "Population Shares" and "Program Enrollment". δ_i and ϵ_{it} are the prison fixed effect and an *iid* error term, respectively. Columns 3 and 4 of Table 5 also include either time fixed effects or a flexible time trend in the specification.

This estimation strategy relies on the identifying assumption that $E(\epsilon_{it}|t, Treat_i, X_{it}) = 0$. The intuitive interpretation of that assumption, as it pertains to AB 109, is that any systematic variation in the rate of violence pre- and post-implementation, beyond that induced by the shock to crowding, is uncorrelated with the pre-implementation shares of the treatment populations. However, the assumption in this case must allow for at least some minimal control variables, X_{it}, which is necessary to account for the reception adjustment and the fact that changing population shares are correlated with implementation of AB 109.

Table 4 provides a view of the data broken down before and after treatment for each of the different treated populations. The groups are the same as those in Figure 6 and thus do not align directly with the model in Equation 2, since the latter uses shares rather than a discrete indicator of treatment. Table 4 illustrates a number of things about the different treatments. All three treatments see a decrease in the average rate of assault in the post periods, but only marginally so for the reception group. In addition, there are notable differences in the baseline rates of assault between the groups, which follow a predictable pattern. Assaults are most common in the control group because most of the state's security level 4 population is incarcerated in those prisons. Reception centers are also prone to higher levels of misconduct, ostensibly because the perpetual turnover is disruptive to mechanisms of informal governance. Average differences in the rates of assault across these groups are generally stable over time, with the exception that reception centers do have greater time variation than other populations.

The highlighted row in Table 4 for *crowding* shows that all three treatment groups experience a similar decrease in crowding and it is much larger than the decrease in the control prisons. This further supports the earlier claim that the reception adjustment was a sufficient response to

Table 4: Pre and Post Statistics by Treatment Group

	Control Group		Reception Group		Level 2 Group		Level 3 Group	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Violence								
Rate of Assaults	0.71	0.71	0.70	0.66	0.32	0.27	0.51	0.40
	(0.41)	(0.44)	(0.29)	(0.32)	(0.21)	(0.23)	(0.32)	(0.24)
Total Assaults	27.94	25.17	34.79	27.47	17.89	13.01	22.55	15.08
	(14.62)	(14.30)	(14.76)	(13.76)	(12.02)	(11.41)	(13.45)	(8.53)
Assaults on Inmates	21.81	18.97	27.39	23.12	14.61	10.69	17.95	12.01
	(13.06)	(12.28)	(13.80)	(13.18)	(10.13)	(9.82)	(12.27)	(7.74)
Assaults on Staff	6.13	6.20	7.40	4.34	3.28	2.32	4.60	3.07
	(4.96)	(7.59)	(5.25)	(2.81)	(3.49)	(2.51)	(5.20)	(3.41)
Crowding								
Crowding (P/K)	1.77	1.61	2.06	1.70	1.96	1.66	1.99	1.68
	(0.25)	(0.23)	(0.21)	(0.20)	(0.20)	(0.21)	(0.20)	(0.17)
Total Population (P)	4132.62	3740.85	5065.20	4213.28	5493.77	4671.10	4691.94	3985.47
	(816.58)	(670.22)	(684.79)	(817.66)	(1057.11)	(970.41)	(1084.07)	(1040.11)
Design Beds	2390.71	2288.49	2462.17	2395.36	2853.50	2749.36	2404.84	2286.36
	(609.32)	(568.37)	(414.08)	(417.62)	(623.83)	(591.01)	(609.38)	(643.45)
Subpopulations								
Level 1	718.81	619.01	580.73	521.27	607.61	548.91	352.21	263.08
	(1133.89)	(1043.51)	(624.99)	(720.92)	(948.91)	(909.85)	(264.07)	(220.14)
Level 2	219.69	137.55	496.30	571.23	2907.98	2540.53	842.06	706.93
	(357.78)	(319.39)	(653.22)	(745.82)	(1405.96)	(1147.00)	(1148.23)	(1032.20)
Level 3	298.98	175.03	236.28	622.53	976.08	920.69	2432.76	2040.53
	(336.73)	(271.48)	(327.86)	(530.68)	(1171.54)	(1025.45)	(773.24)	(557.59)
Level 4	2183.19	2158.75	356.33	450.18	230.17	190.08	423.16	533.76
	(1165.56)	(1125.70)	(571.30)	(927.09)	(578.40)	(572.22)	(461.50)	(514.26)
Reception	72.35	26.65	2855.43	1528.01	372.41	118.45	174.23	56.50
	(178.73)	(87.92)	(1212.16)	(1481.51)	(767.12)	(315.42)	(551.91)	(232.59)
Special Needs	683.94	628.47	578.55	906.38	1302.55	1421.83	907.52	1076.85
	(653.53)	(614.05)	(826.60)	(1054.63)	(1177.03)	(1249.39)	(1115.88)	(1059.35)
Programs								
Prison Industries	22.44	7.80	167.78	122.53	264.08	230.67	242.29	221.54
	(38.10)	(14.02)	(104.32)	(77.21)	(185.10)	(172.39)	(190.25)	(176.44)
Academic	406.55	340.47	172.55	162.53	639.61	480.46	480.33	401.21
	(222.53)	(141.21)	(184.05)	(134.68)	(391.83)	(199.87)	(286.15)	(180.21)
Non-PIA Work	1997.30	1724.30	1346.78	1195.29	3364.15	2839.77	2536.09	2177.30
	(1014.45)	(921.60)	(818.91)	(617.45)	(1096.89)	(875.37)	(882.35)	(784.79)
Subst. Abuse	13.10	0.00	94.13	32.35	294.83	104.55	92.94	30.92
	(54.45)	(0.00)	(137.12)	(56.70)	(379.89)	(58.44)	(136.25)	(50.87)
Subst. Abuse Waitlist	8.50	0.00	67.12	72.66	121.84	156.62	42.87	67.18
	(37.34)	(0.00)	(117.82)	(159.85)	(113.53)	(115.08)	(85.39)	(118.51)
Observations	273	105	312	120	390	150	429	165
Number of IDs	7	7	8	8	10	10	11	11

Means reported. Standard deviations are in parenthesis. Treatment groups defined by > 20% share of the given population.

diminish the reception center impact of AB 109 to a level similar to that in level 2 facilities and simultaneously create a similar magnitude shock to crowding in level 3 facilities. The effect on level 3 populations is also visible in the other highlighted sections of the table, which show the level 3 population experience an approximately equivalent increase and decrease in the reception group and level 3 group, respectively.

To review, Table 4 and figures in Section 3 demonstrate that each of the three AB 109 treatments provide the crucial variation in crowding necessary to identify the relationship with violence. Meanwhile the compositional mechanism proposed in Section 4 implies a form of omitted variable bias for any estimates relying on these reductions in crowding. However, it is further implied that the expected bias in the level 2 treatment should be minimal, or possibly even absent, while the expected bias for the reception treatment is larger and potentially quite significant. Minimal bias for the level 2 treatment relies on similarities between the the base population and that which is targeted by AB 109, which requires some efficacy to the selection by which security classification is determined (evidence of this is clear in Table 9). The implication for the level 3 treatment is not immediately obvious since nothing is known about the selection process by which prisoners were chosen for transfer to repurposed reception facilities. Indeed it is quite possible that very different selection criteria were used by officials at different prisons, as opposed to the very uniform selection criteria that AB 109 implemented for reducing the overall population. Uncertainty about the exact form of selection in the level 3 treatment indicates that the estimates for this group will not be particularly informative, but nonetheless need to be included in the identification strategy to control for the fact that these populations were subject to a simultaneous treatment.

DD Estimates

Table 5 shows the β_1 coefficient for each of the three AB 109 treatments. As mentioned previously, indicators for the timing of reception adjustment are always included as controls and X represents a full set of controls including population shares and program participation. Columns (3) and (4) are two different extensions of the specification in column (2). Column (3) adds time fixed effects while column (4) adds a flexible time trend and omits the first three months of post-treatment observations. In all specifications standard errors are clustered at the prison level and each observation is weighted by the average population size of that prison measured over the six

Table 5: Difference-in-Differences Estimation

Dependent Variable: Log Rate of Assaults

	(1)	(2)	(3)	(4)
VARIABLES	Base	Controls	TimeFE	3mo.Gap
TreatLv2*Post	-0.529***	-0.388**	-0.390***	-0.446***
	(0.176)	(0.142)	(0.122)	(0.159)
TreatLv3*Post	-0.303	-0.211	-0.206	-0.306
	(0.279)	(0.271)	(0.144)	(0.310)
TreatRec*Post	0.252	0.272	0.218	0.471***
	(0.191)	(0.179)	(0.173)	(0.127)
Observations	1,470	1,470	1,470	1,380
Controls	RA only	X	X	X
Trend/Gap	No	No	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

months prior to AB 109 implementation.

The relationship between pre-treatment share of level 2 population and violence is consistently negative and quite large. On the other hand, the coefficients for the other two treatments are either not significant or even positive. Yet the positive coefficient on the reception treatment is consistent with a large compositional effect driving an increase in assaults that overwhelms any decrease from reduced crowding. Examining columns (2) and (4) reveals that omitting the few months of AB 109 prior to the reception adjustment increases both the magnitude and significance of the point estimate for the reception treatment. This also aligns with the implications of the model in Section 4 since the omitted months in column (4) are the months for which crowding effect (decreasing violence via $E_{V;c} > 0$) as well as the compositional effect (increasing violence via $E_{\pi;\lambda} < 0$) can both be expected to be quite large. By contrast, during the later months the reception adjustment offsets much of the decreased crowding but the change in composition is sustained, making the expected compositional effect stronger relative to the crowding effect.

The point estimates for the level 3 treatment are negative and qualitatively similar to the level 2 estimates but with large standard errors. Since the nature of the compositional bias in the level 3 treatment is unknown, it is difficult to gage the informative value of the resulting point estimates. However, they do not contradict the evidence embodied by the coefficient for the level 2 treatment.

Absent the theory of compositional change, the estimates in Table 5 suggest that the decrease in crowding due to AB 109 led to a decrease of approximately 40% in the rate of assaults at level 2 facilities. The level 2 facilities saw crowding fall about 30 percentage points from an initial point of almost 200% of design capacity, implying a semi-elasticity of approximately 1.3 for this specific type of prison population. On the other hand, there is no clear effect and possibly an increase in assaults for the reception center populations. It is possible that this is due to some fundamental difference between reception centers and level 2 facilities, either with regard to the populations themselves or the housing and security protocols. Yet it is also true that the difference in estimates for the level 2 and reception populations comport well with the assumption that there is compositional element to the population shock generated by AB 109, because such compositional change would be necessarily more significant among the reception population. The results can thus be interpreted as descriptive evidence supporting the presence of such a compositional effect.

6.2 Instrumental Variable (IV)

$$\hat{C}_{it} = \alpha_0 Months_t + \alpha_1 Months_t^2 + \alpha_2 Months_t * S_i^n + \alpha_3 X_{it} + \alpha_4 f(t) + \gamma_i + u_{it} \tag{3}$$

$$Y_{it} = \beta_0 + \beta_1 \hat{C}_{it} + \beta_2 X_{it} + \beta_3 f(t) + \delta_i + \epsilon_{it} \tag{4}$$

Equations 3 and 4 present the basic structural form of the IV strategy. Equation 3 is the first stage estimating equation wherein crowding is estimated as a function of the number of months since the implementation of the policy, $Months_t$, interacted with the pre-implementation shares, S_i^n, of population type n. In the baseline IV, only initial population shares for the treated subpopulations are used as instruments. Specifications tested with an expanded set of instruments find only minor adjustments to the coefficient of interest. Equation 4 is the second stage estimation, which is a fixed effects regression of the rate of assaults on the predicted values of the crowding variable. The estimation includes the same control variables included in the main DD specification[20]. A polynomial time trend is included in each stage of estimation.

In effect, the IV strategy uses the time since implementation of AB 109 and the initial share of

[20]These include indicators for the timing of the reception adjustment and the population share and program enrollment variables included in Table 1.

each population type to predict the change in crowding at each prison[21]. This approach exploits the same exogenous variation as the DD approach but allows flexibility in modeling variation in the intensity of treatment over time. The IV strategy also has the benefit of added flexibility in modeling the impact of the reception adjustment. Specifically, the "Interact RA" specification in Table 6 allows the degree to which pre-shock reception share predicts changes in crowding to be diminished as the reception adjustment occurs in the given prison. The major shortcoming of the IV specification is that it necessarily conflates any compositional bias from any of the three treatments into the estimated effect of crowding on the rate of assaults.

The exclusion restriction for this IV strategy requires that the pre-shock composition of prison populations is uncorrelated with future variation in the rate of assault and battery, other than through it's correlation with changes in the level of crowding due to the policy design. The only clear challenge to the validity of this restriction is the afore mentioned fact that pre-AB 109 population shares are correlated with the post-AB 109 changes in those shares. For this reason all specifications of the IV model include a full set of controls than include contemporaneous population shares for each subpopulation.

IV Estimates

Table 6 provides the estimated $\hat{\beta}_1$ for a number of variations on the IV model. A benefit of the IV model is the straightforward interpretation of the $\hat{\beta}_1$ coefficient. It is a semi-elasticity showing the marginal effect of crowding on the rate of assaults, where crowding is measured in percentage point changes and the rate of assault in percent changes. The first column of the table is the base specification of the model, exactly as presented in equations 3 and 4. The other three columns each represent a different variation from the base specification. The second column includes an additional term in the excluded instruments, which interacts the RA_{it} variable[22] with the $Months_t * S_i^n$ term of the reception treatment. Column (3) is a robustness check that removes the $Months$ terms that are not interacted with population shares from the IV exclusions, allowing that there may be some statewide correlation between the policy timing and assaultive behavior. The standard error inflates slightly with this change, but the coefficient remains large and statistically significant. In

[21] These population shares are defined as the population of type n divided by the total prison population, averaged over the 6 months preceding implementation of AB 109.

[22] RA_{it} is an indicator that turns on in the month that prison i has the reception adjustment.

Table 6: IV Model with Prison Fixed Effects

Dep. Variable: Log of Assaults and Batteries per 100 inmates				
	(1)	(2)	(3)	(4)
VARIABLES	Base IV	Interact RA	Exclusion	Drop 3mo.
Crowding (P/K)	2.117***	1.548***	1.718**	2.289***
	(0.627)	(0.497)	(0.767)	(0.629)
Observations	1,440	1,440	1,440	1,350
Number of ID	30	30	30	30
Controls	X	X	X+Months	X
Exclusions	Basic	Months*S*RA	Months*S	Base
F test IVs	10.34	26.81	10.05	10.59

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

the final column the 3 month period just following implementation and preceding full scale reception adjustment is excluded from the analysis. This is an alternate means of accounting for the effects of the reception adjustment, so the RA control variable is excluded from the specification in column (4).

A few things are immediately observable from these results. First, a comparison of these estimates with the earlier OLS estimates shows evidence of significant downward bias in the OLS estimates, likely due to endogeneity as discussed earlier. The estimates from each of the IV specifications are large, statistically significant, and reasonably stable. These estimates are possibly subject to significant attenuation due to compositional bias, yet still exhibit semi-elasticities as high 2.2. The more conservative estimate in column (2) suggests that decreasing crowding by 10 percentage points can decrease the rate of assault by as much as 15 percent.

The difference between the column (1) and (2) estimates is also of interest. The two estimations are identical beyond the one addition of the interaction $Months_t{*}S_i^R{*}RA_{it}$. As discussed previously, this interaction provides a greater ability to predict changes in crowding using the pre-shock share of reception population. In the absence of this interaction, the controls for administrative response only allow for a level shift in crowding once there has been a response. In the first stage regression coefficients (available in Table 10 in the appendix), the point estimate for the coefficient on this interaction is almost precisely the same magnitude as the $\hat{\alpha}_2$ for reception share, which is the negative of the former. This implies that the pre-shock share of reception population correctly predicts decreases in crowding when AB 109 begins and up until the reception adjustment occurs, at which point it ceases to have any predictive power at all because the two coefficients cancel each other out. This improved fit in the first stage modeling of crowding via the reception share together with the diminished coefficient in Table 6, aligns with the results from the DD strategy that reception centers do not see assaults decrease to the degree, if at all, that the other treated facilities do.

6.3 Tests & Robustness

Section 2 presents the argument that previous research has struggled to identify a consistent correlation between prison crowding and violent behavior. Further, because of the correlational nature of much of the existing research, the inconsistency between studies implies that even when a positive correlation is identified it is as likely due to spurious correlation or publication bias as any true relationship. This research contributes to the literature estimates driven by AB 109, a court mandated policy shock that directly impacted the level of crowding in California prisons; AB 109 provides rationale for the position that the estimates in this paper are unbiased evidence of the causal effect of crowding on violent behavior. Yet a plausible source of bias remains, namely the compositional effect defined in Section 4. However, the compositional effect is reasonably expected to bias estimates towards zero and thus at worst the estimates in this paper would be a lower bound on the true value. Still the limitations of these data and the exogeneity of the AB 109 intervention do warrant some further discussion.

The first concern pertains to the validity of the channel by which the instruments and DD design identify the effect of crowding on violence. Although it is certainly the true that AB 109 reduced crowding, it remains a possibility that there is some spurious artifact of the assault data driving the results or some unknown features to the implementation of the new law that were the real causes of reduced violence. For example, the inability to control for staffing changes, due to limitations of these data, is a potential concern. Furthermore, even if staffing changes were insignificant[23], it is possible that staff were simply able to operate more effectively once there were fewer inmates

[23] Although the available data on staffing has missing data and other issues that make the author uncomfortable including staffing variables in this research, a general read of the existing data suggests that staffing changes due to AB 109 were minor.

Table 7: IV Model: Testing other measures of misconduct.

Dep. Variable: Log-rate of the given form of misconduct.

VARIABLES	(1) Assaults	(2) Incidents	(3) Drugs	(4) Cellphone
Crowding (P/K)	1.522***	1.406***	0.418	-0.0583
	(0.558)	(0.312)	(0.761)	(0.810)
Observations	750	750	750	750
Number of ID	30	30	30	30
Controls	X	X	X	X
Exclusions	Basic	Basic	Basic	Basic
F test IVs	16.91	16.91	16.91	16.91

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

crowding the facilities. Yet if the policy induced variation in assaults were due to enforcement gains from improved staffing ratios or effectiveness of staff then the estimated effects should be present for other forms of misconduct as well.

Table 7 confronts the above concerns by repeating the IV specification with different measures of misconduct. Some of these measures were not recorded in the early years of CompStat data, so the number of pre-AB 109 observations in this table are limited to 15 months. Column (1) repeats the IV specification from column (2) of Table 6 for the limited time period of the other specifications here, showing a qualitatively identical estimate to those in Table 6. Column (2) replaces the measure of assaults, previously disciplinaries, with the "incidents" measure of the same type of violation. The point estimate is not sensitive to the which measure of assaults is used. In stark contrast, columns (3) and (4) prove there is no identifiable impact on other forms of misconduct that occur with similarly high frequency to that of assaults.

The validity of using the variation in crowding from AB 109 is further tested in Table 8. Column (1) is a replication of column (1) from Table 6 and each of the following columns repeats the model with the policy implementation beginning the specified number of months earlier than the true implementation date of AB 109. To maintain comparability of the estimates, the data is truncated in each specification so the number of post-implementation months remains constant. Since there was no equivalent in these periods to the reception adjustment that occurred following AB 109,

Table 8: IV Model: Placebo tests with policy implementation at alternate dates.

Dep. Variable: Log of Assaults and Batteries per 100 inmates					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Base IV	9 Month	15 Month	21 Month	27 Month
Crowding (P/K)	2.117***	1.891	0.791	0.356	0.195
	(0.627)	(1.998)	(1.097)	(0.901)	(2.196)
Observations	1,440	1,140	960	780	600
Number of ID	30	30	30	30	30
Controls	X	X	X	X	X
Exclusions	Basic	Basic	Basic	Basic	Basic
F test IVs	10.34	2.874	5.248	2.761	2.054

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

the *RA* variable is omitted from the lagged specifications. The results are no different if the *RA* control is reintroduced into the estimating equations. None of the resulting estimates are close to statistical significance in either the first or second stage regressions.

Tables 7 and 8 both rely on the IV strategy to test their respective alternate hypotheses. This approach is more direct and has the benefit of reporting fewer coefficients, whereas the multiple coefficients reported in the DD strategy increases the risk of spurious statistical significance. In addition, the less refined modeling of time variation in the DD strategy is more likely to pick up correlations from any of several earlier, less dramatic policy changes that occurred in the years leading up to AB 109.

It is also possible that while overall variation in crowding from AB 109 is appropriately exogenous, the subpopulations used to identify the intensity of crowding reductions are not the proper channel. The likely alternative is that prison administrators were able to manipulate new prisoner classifications to reduce populations in facilities that were the most crowded, rather than those naturally targeted by reducing the inflow of non-violent offenders. The result of this would be that initial crowding should do a better job predicting the post-AB 109 reductions in crowding than the pre-shock population shares do.

Figures 7 and 8 depict the relationship between the initial level of crowding and change in crowding, with Figure 8 breaking the trends up by the same rough treatment groups used in Table

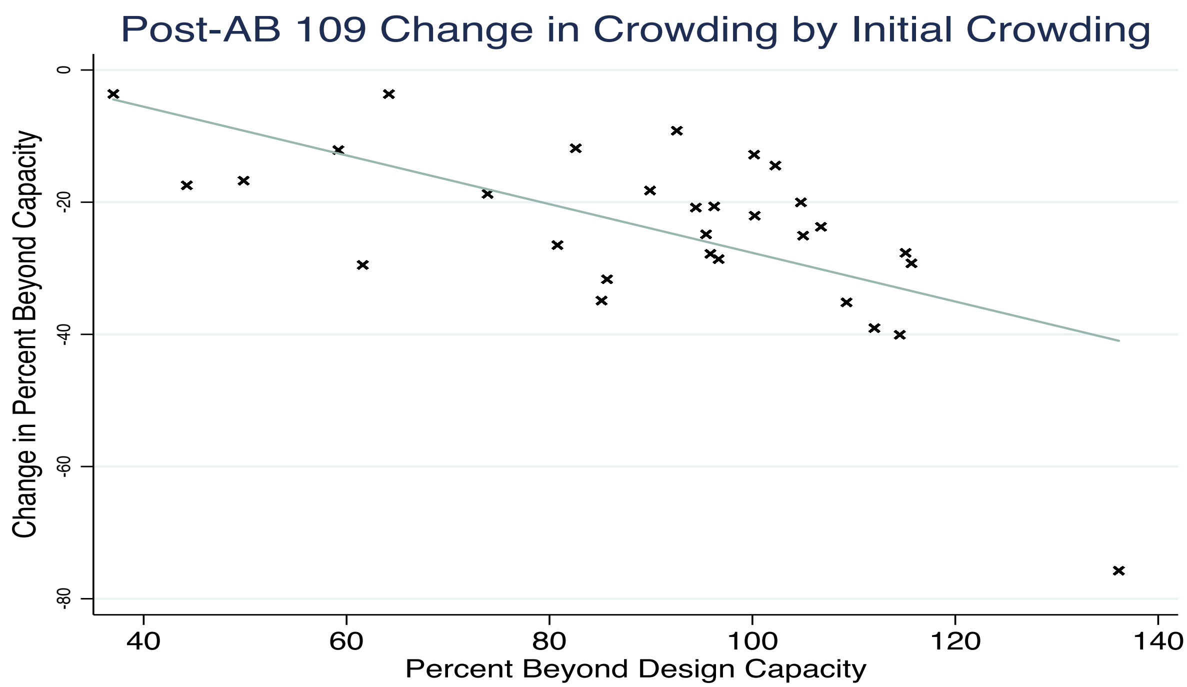

Figure 7: *This figure shows the correlations between initial crowding and the decrease in crowding after implementation of AB 109.*

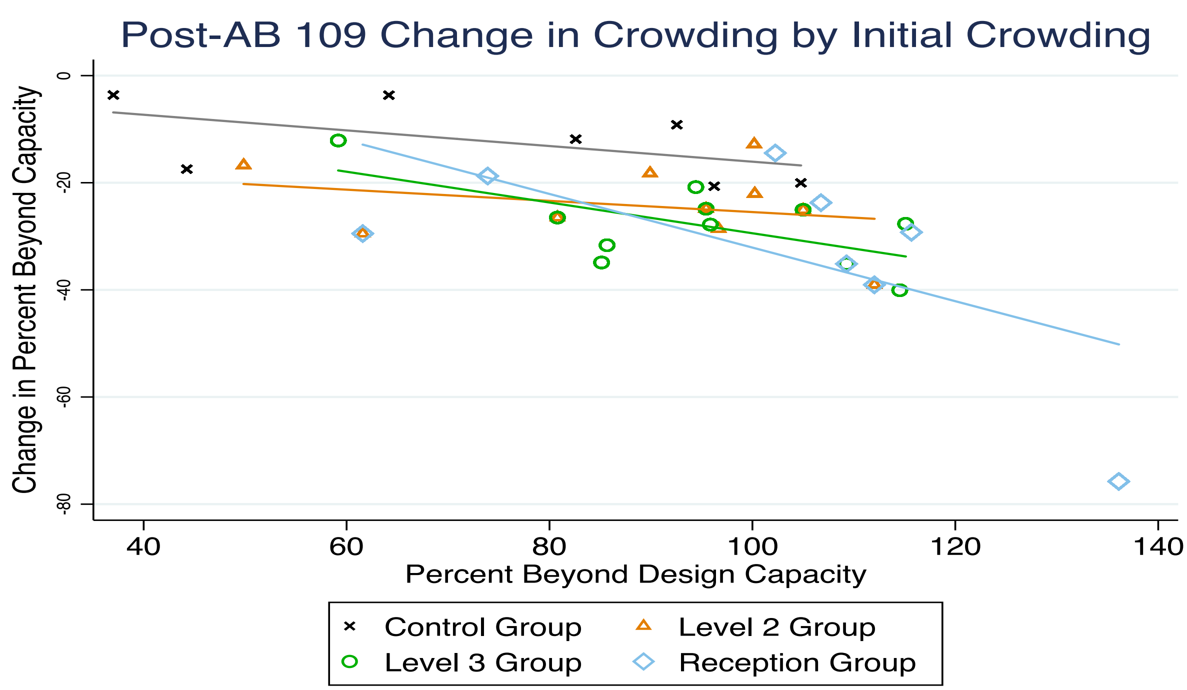

Figure 8: *This figure shows the correlations between initial crowding and the decrease in crowding after implementation of AB 109, separated by "treatment groups". It shows that the apparent correlation between the variables in Figure 7 is due to the fact that the treated populations were, on average, those that were more crowded to begin with.*

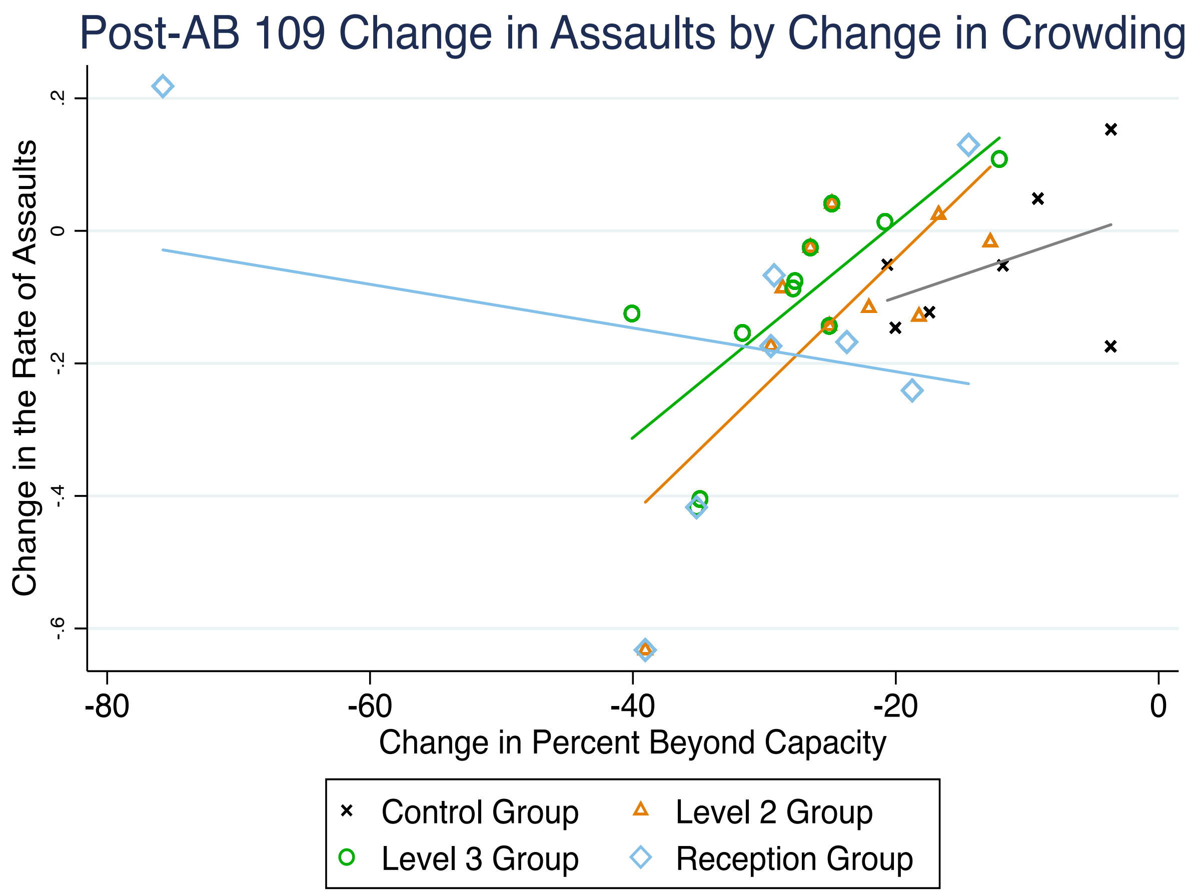

Figure 9: *This figure shows the correlations between change in crowding and the change in the rate of assault following implementation of AB 109, separated by "treatment groups".*

4 and Figure 6. If the above concern were valid, then the correlation apparent in Figure 7 would remain mostly intact in Figure 8, with the treated populations simply having systematically higher levels of initial crowding (which would then induce the larger reductions seen for those groups in Table 4). Instead the fitted lines for each group in Figure 8 have relatively shallow gradients and those observations in the treatment groups with less crowding saw larger reductions than comparable prisons in the untreated group. The exception to the shallow slopes in Figure 8 is the line for the reception group, for which the fitted line retains a slope similar to that in Figure 7. However, note that the slope for the reception group is driven by the single outlier in the bottom right of the figure[24]. With the outlier removed, the reception line has a slope as shallow as any of the others. In sum, when treatment groups are accounted for there is still a weak correlation between initial crowding the the reduction induced by AB 109, but the treated subpopulations appear to be an appropriate predictor of changes in crowding.

A final issue for discussion is the omitted outlier from Figure 6. The omission has a significant impact on the presentation of that figure, which is shown by Figure 9. The outlier, DVI, experiences the largest reduction in crowding among the prisons but also experiences the largest *increase* in assaults, which dramatically alters the fitted line for the reception group. A brief investigation of this did not reveal a clear reason for the distinct experience of DVI relative to the other prisons. As such, DVI was not excluded from any of the empirical specifications in this section, only the earlier figure to better illuminate the consistent relationship in the data. However, it is also of note that exclusion of DVI does not qualitatively change any of the empirical estimates. Table 11, in the appendix, demonstrates this by replicating the full set of DD specifications with DVI excluded from the analysis.

7 Conclusion

Violent behavior in prisons may be caused by a variety of mechanisms. In line with much of the literature (Kearney et al., 2014), this paper examines the role of prison crowding as a determinant of violence. This relationship plays an important role in well-informed policy decisions and its

[24]The outlier in this figure is again DVI, the same prison that was omitted from Figure 6

study is particularly apropos given recent political movements to reduce mass incarceration in the United States.

Although theory and popular opinion have long held prison crowding as a key determinant of violent behavior, empirical estimates in the existing literature have been surprisingly inconsistent (Franklin, Franklin, & Pratt, 2006). The estimates in this paper are the first to use a quasi-experimental design that specifically targets the effect of crowding on violence. These estimates represent persuasive evidence of a causal effect of crowding on violent misconduct that is positive and qualitatively large. They suggest a 10 percentage point decrease in prison crowding results in a decrease in the rate of violent assaults by approximately 15%, which could imply significant cost savings associated with reductions in crowding. A careful review of the empirical results also provides evidence that the compositional effect defined in Section 4 is indeed a factor in the outcomes from the AB 109 shock to crowding. This further implies that the compositional effect is a plausible factor to be considered with regard to previous and future empirical work on crowding and violence. The compositional effect, as a new source of potential bias, adds a nuanced explanation for conflicting evidence in existing empirical research on crowding and violence.

There are some natural limits to the implications of this research in policy application. Foremost among these is external validity when considering dissimilar prison populations. Although the IV strategy incorporates some statewide variation in crowding across prisons, the estimates are largely driven by variation in security level 2 populations. These populations have relatively low rates of violent misconduct and it is possible that prison populations with a higher propensity for violence could be either more or less responsive to changes in crowding. The DD estimates for the other treated populations do little to better inform this issue since both are expected to be subject to greater compositional bias than the level 2 treatment. It is also important to recognize that the identifying variation for this research is from very high levels of overcrowding, many of the affected facilities beginning well above 200% capacity prior to implementation of AB 109[25]. It is reasonable to expect some variation in the marginal impact of crowding on violent behavior when examining the relationship in much less crowded facilities.

In summary, this research offers several unique contributions to the literature. It presents the first empirical evidence of a strong causal effect of prison crowding on violent misconduct. It

[25]The initial levels of crowding can be observed along the horizontal axis in Figures 7 and 8.

also introduces the idea that there is a compositional element to policy interventions that reduce crowding, which can lead to bias in empirical estimates. Although this concept is not necessarily novel, having come up in many of the author's conversations on the topic, this paper is the first to formally discuss the idea and its role in studying prison crowding and violence. Finally, this work highlights many areas of opportunity for subsequent work studying prison violence.

One issue to be further addressed in future research is heterogeneous effects among different types of prison populations. As mentioned to earlier, the estimates in this paper are mostly pertinent to prison populations that are relatively less prone to violence and prison settings that are subject to extreme levels of crowding. Maximum security facilities are of particular interest in this regard, both because they have the highest baseline rates of violence[26] and because housing and security protocols in such facilities tend to be quite different from other prison facilities.

Another important extension of this research will be to access improved data to allow an in depth analysis of the interaction of the compositional and crowding effects from changes in prison populations. With sufficiently detailed individual inmate data, a full decomposition of the respective mechanisms is possible and will allow a much more nuanced understanding of policy impacts on violent misconduct. This information could be an invaluable contribution to social, political, and administrative insights regarding the costs and benefits of a broad variety of justice related policy reforms.

[26]Security level 4 facilities in California have significantly higher rates of violence than other facilities, show in Table 9.

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A Theory Appendix

Return to Section 4.

The objective of this model is to capture the major channels by which policy interventions that increase or decrease the population (and thus crowding) may impact violent behavior in prisons. The main channel of interest is the role of changing the composition of the prison population with regards to individuals' tendency to resort to violence. To this end, it is not the intent of this model to explore the motives underlying individual choices. Nor is it intended that the model capture the determinants of all forms of violent behavior. Since premeditated assaults and strategic gang violence are unlikely to be responsive to the crowdedness of the prison, the model is oriented to violent behavior may be seen as impulsive or extemporaneous.

Recall that the three mechanisms defined in Section 4 were a behavioral mechanism, a structural mechanism, and a compositional mechanism. The setting is distilled into a reduced form, applied probability model where pairwise interactions occur between inmates. These interactions are assumed to be contentious in nature and each has a probability of resulting in violence. Since the interest of this model is the effect of changing the composition of a set of heterogeneous individuals, the underlying rational choice problem of each individual is suppressed in this presentation of the model[27]. Instead, each individual is assumed to have a baseline *propensity* for violence, a_i, that is distinct from their *probability* of resorting to violence in any given situation. Propensity is assumed to be a fixed individual characteristic, whereas the probability is a function of situational factors (e.g. crowding) and the individual's fixed propensity. However, it is the overall rate of violence for the prison population that is modeled in this appendix, so the implications of these individual propensities are aggregated to the prison level variables in the following model set up.

V *Total violence per unit time.*

P *Total prison population.*

K *Design capacity of the prison.*

c *Degree of crowding, defined as the population/capacity ratio (P/K).*

s *Scale effect as a function of P, generally taken to exhibit constant returns to scale.*

[27] Future work on this research will include treatment of the underlying choice setting for inmates, as well as the strategic interaction between inmates that leads to taunting and baiting their opponents. As it pertains to the broader idea of compositional change, the author does not believe those stages to be instrumental.

n *Number of potentially violent interactions per unit time for each individual, with* $n'(c) \geq 0$.

π *Probability that a particular interaction will be violent, with* $\pi'(c) \geq 0$.

λ^n *A shift parameter for policy 'n' with a positive relationship to crowding.*

a_i *An index measuring individual i's baseline propensity for violence.*

$F(\cdot)$ *The distribution of all inmates'* a_i*, with support* $[0, 1]$[28].

Given this setting, the aggregate incidence of violence in the prison is defined by the identity in Equation 5. The equation simply states that the total violence in a unit of time will equal the total number of pairwise interactions that occur per unit time[29] multiplied by the average probability that a single interaction becomes violent. This very basic representation of the setting allows the structural crowding mechanism to be captured by $n(c)$. Meanwhile $\pi(c, \lambda^n)$ captures both the behavioral and compositional mechanisms, respectively the direct effect of c and the marginal effect of the shift parameter λ^n.

$$V = [s(P)][n(c)][\pi(c, \lambda^n)] \tag{5}$$

To derive the responsiveness of violence to crowding and incorporate the principle that changes in crowding are the result of some policy change, it is assumed that crowding (and thus total population) is a function of the policy parameter (λ^n) with an elasticity of one ($E_{c:\lambda^n} = 1$). Furthermore, we allow that the relationship between the shift parameter (λ^n) and probability of violence ($\pi(\cdot)$) can vary between policy options. That is, the partial derivatives $\frac{\partial \pi}{\partial \lambda^1} < 0$ and $\frac{\partial \pi}{\partial \lambda^2} > 0$ are explicitly permitted in this setting.

The elasticity of violence with respect to a population shock is derived as follows.

$$\begin{aligned} V &= s(P)n(c)\pi(c, \lambda^n) \\ &= s(cK)n(c)\pi(c, \lambda^n) \\ \implies ln[V] &= ln[s(cK)] + ln[n(c)] + ln[\pi(c, \lambda^n)] \\ \implies \frac{1}{V}\frac{dV}{d\lambda^n} &= \frac{1}{s(P)}s'(P) \cdot K\frac{dc}{d\lambda^n} + \frac{1}{n(c)}n'(c)\frac{dc}{d\lambda^n} + \frac{1}{\pi(c, \lambda^n)}\left[\frac{\partial \pi}{\partial c}\frac{dc}{d\lambda^n} + \frac{\partial \pi}{\partial \lambda^n}\right] \end{aligned}$$

[28] $F(\cdot)$ is an approximation of the true distribution from which an inmate's "partner" in any pairwise interaction is randomly is randomly drawn. For sufficiently large populations, the distributions are effectively identical.

[29] Under CRS, $s(P) \cdot n(c)$ can be simplified to just $P \cdot n(c)$, which is the total population times the number of interactions per individual per unit time.

Then multiply through by λ^n.

$$\begin{aligned}
\frac{\lambda^n}{V}\frac{dV}{d\lambda^n} &= \Big[\frac{1}{s(P)}s'(P)\cdot K + \frac{1}{n(c)}n'(c) + \frac{1}{\pi(c,\lambda^n)}\frac{\partial \pi}{\partial c}\Big]\frac{dc}{d\lambda^n}\frac{\lambda^n}{c}c + \frac{\lambda^n}{\pi(c,\lambda^n)}\frac{\partial \pi}{\partial \lambda^n} \\
\implies E_{V:\lambda^n} &= \Big[\frac{1}{s(P)}s'(P)\cdot K + \frac{1}{n(c)}n'(c) + \frac{1}{\pi(c,\lambda^n)}\frac{\partial \pi}{\partial c}\Big]c\cdot E_{c:\lambda^n} + E_{\pi:\lambda^n} \\
&= \Big[\frac{cK}{s(P)}s'(P) + \frac{c}{n(c)}n'(c) + \frac{c}{\pi(c,\lambda^n)}\frac{\partial \pi}{\partial c}\Big]E_{c:\lambda^n} + E_{\pi:\lambda^n} \\
&= \big[E_{s:P} + E_{n:c} + E_{\pi:c}\big]E_{c:\lambda^n} + E_{\pi:\lambda^n}
\end{aligned}$$

Now recall that λ^n is defined such that $E_{c:\lambda^n} = 1$ and note that constant returns to scale[30] requires that $E_{s:P} = 1$. Then the total policy impact can be decomposed into the scale effect plus an elasticity that represents each of the three mechanisms, as shown in Equation 6.

$$E_{V:\lambda^n} = 1 + E_{n:c} + E_{\pi:c} + E_{\pi:\lambda^n} \tag{6}$$

The first terms on the righthand side of Equation 6 constitute the direct elasticity of violence with respect to crowding, $E_{V:c}$. Therefore Equation 7, the same as presented in Section 4, is an equivalent representation of the relationship between violence and the policy parameter.

$$E_{V:\lambda^n} = E_{V:c} + E_{\pi:\lambda^n} \tag{7}$$

There is much yet to be discovered about the motivations and determinants of violent behavior, in and out of prisons. What is offered here is the simple insight that there are several potential mechanisms at work that determine the net effect of changing prison crowding on violent behavior. Furthermore, with sufficiently rich data, it should be possible to perform a decomposition of the overall impact of a policy intervention and differentiate between these mechanisms. Lastly, in the absence of very granular data, estimates using any significant variation in crowding should be viewed as estimates of the relationship represented by $E_{V:\lambda^n}$ and not $E_{V:c}$.

There is an argument to be made that the latter point is not necessarily an issue. For example, in a study that is a straightforward impact evaluation following a new law or regulation, the effects of each mechanism are all part of the impact that the law had on violence and thus rightfully

[30] CRS in this setting implies that, in the absence of any crowding or compositional changes, doubling the population size will double the total amount of violence.

included in the analysis. The caution raised by this model is in proper interpretation. AB 109 and the results of this research provide a poignant example of this. Separate impact evaluations for reception centers and level 2 facilities would likely show no significant impact on violence in the former and a decrease in the rate of violence for the latter. Attributing these directly to crowding would imply that violent behavior in reception populations is not responsive to crowding. While the model presented here does not preclude that possibility, it does raise a plausible alternate explanation that simultaneously accounts for the difference in outcomes at level 2 facilities.

The framework is also helpful for conceptualizing the role that the design of an intervention plays. The impact of AB 109 on reception centers is a good case of this. In the initial stage, AB 109 dramatically reduces crowding in reception facilities and does so by eliminating the flow of incoming non-violent offenders. Since reception centers take custody of all other offenders upon arrival in the prison system, now mostly very serious offenders, it can be expected that there is a significant compositional change in addition to the large decrease in crowding. These are expressed in Equation 6 as $E_{n:c} > 0$ and/or $E_{\pi:c} > 0$ from the crowding mechanisms and $E_{\pi:\lambda^n} < 0$ from compositional change. But there is also the reception adjustment, which consolidates the remaining reception populations into fewer facilities. This diminishes the overall drop in crowding, which pertains to the first two elasticities, but maintains the compositional change associated with the very large reduction in total reception population size, which acts through the latter elasticity.

In summary, empirical work on the relationship between prison crowding and violence typically claims to estimate that relationship directly. The model presented here questions whether that is really the case, based on two assumptions: there is hetergeneity among inmates with regards to their propensity for violence and increasing or decreasing crowding is associated with altering the composition of the inmate population with respect to this heterogeneity. Where possible a decomposition of the policy effects on violence should be performed to properly illuminate the distinct roles of crowding and composition. With less precise data, logic dictates that some policies will have a predictable pattern of selection by which they cause compositional change and this can be used to make inferences about the manner in which compositional change may bias estimates from the data.

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B Empirical Appendix

This appendix provides figures and regression estimates that have been excluded from the main body of the paper. This additional information tests alternate specifications of the models and provides additional context to the California prison setting.

An interesting piece of context for understanding violence in California prisons is the difference in baseline rates of violence between the subpopulations. Due to the same data limitations with units of observation that constrain the main identification[31], exact averages by subpopulation are not possible. Instead, Table 9 reports a basic OLS regression of the rate of assault on shares of each major subpopulation. The regression is estimated without a constant term, so the point estimates can be viewed as rough approximations of the average rate of assault for facilities with that subpopulation. The negative coefficient on the special needs population emphasizes the fact that there are confounding factors in these approximations. Nonetheless, the estimates follow an intuitive pattern that should be expected. The rates of violence are monotonically increasing in security classification and reception centers fall within bounds set by the security levels. Even high rate at reception centers relative to level 2 and 3 facilities aligns well with the idea that stability in reception centers is disrupted by the high rate of turnover.

Table 10 presents the first stage estimates of the IV specifications from Section 6. The level 2 and level 3 instruments are very consistent predictors of decreased crowding across all specifications. The interesting variation comes in the reception instrument ($Months * Rec$) and the months since implementation variable ($Months$). Adding the additional RA interaction with the reception instrument in column (2) dramatically increases the significance and the magnitude of the coefficient on $Months * Rec$. At the same time, column (2) is the only specification for which $Months$ has little correlation with decreased crowding. Furthermore, the coefficients on the two terms for the reception instrument are the inverse of each other, neatly offsetting one another once a reception adjustment occurs. Together this suggests that the pre-AB 109 reception share is correlated with large reductions in crowding during the early months of the new law, but this correlation dissipates as reception adjustments begin to offset the crowding reductions. When the specifications do not allow for this mid-shock change in the marginal effect of the reception instrument, the correla-

[31] The unit of observation in the data is a prison. Each prison has several facilities that typically house different types of subpopulation, therefore the rate of violence for each prison cannot be attributed to a single subpopulation.

Table 9: OLS Regression of Population Shares on Assaults

Dependent Variable: Rate of Assault per 100 Inmates	
	(1)
VARIABLES	Trend
Security Level 1	0.244***
	(0.0273)
Security Level 2	0.311***
	(0.0179)
Security Level 3	0.623***
	(0.0266)
Security Level 4	1.148***
	(0.0370)
Reception Center	0.934***
	(0.0236)
Special Needs	-0.295***
	(0.0412)
Observations	1,440

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

tion with initial reductions in crowding due to reception share are spread between the reception instrument and the *Months* variable which has a more consistent negative correlation.

Tables 11 and 12 are additional tests of the robustness of the DD estimation strategy. Table 11 simply replicates the Table 5 specifications, but excludes the outlier that is shown in Figure 9 and excluded from Figure 6. The coefficients for the reception treatment are clearly not dependent upon this outlier. Table 12 repeats the DD specification time fixed effects for alternate outcome variables, as Table 7 did with IV strategy. Using incidents rather than disciplinaries to measure assaults undermines the estimates for this strategy. As alluded to earlier, there remain unanswered questions about the selection process by which incidents are reported because they are far less frequent than disciplinaries. The significant coefficient for the reception treatment on drug possession is likely a function of the law disrupting the channels by which contraband is funneled into prisons[32].

Tables 13 and 14 test the effects on the IV strategy of changing the measure of violence. Table

[32]An anecdotal example of this: during an informal interview with a inmate in a California prison, the author was told that one way prison gangs funnel drugs into the prison was to have someone out on parole swallow baggies, then violate their parole to bring them inside the prison. By redirecting parole violators to county jails, AB 109 disrupted the part of the supply chain.

Table 10: 1st stage regressions from IV estimates in Table 6

VARIABLES	(1) Base IV	(2) Interact RA	(3) Exclusion	(4) Drop 3mo.
Months	-0.222**	-0.150	-0.222**	-0.194*
	(0.0958)	(0.0883)	(0.0958)	(0.1000)
Months_sq	0.146*	0.0630	0.146*	0.132
	(0.0793)	(0.0702)	(0.0793)	(0.0853)
Months*Lv2	-0.290***	-0.309***	-0.290***	-0.302***
	(0.0751)	(0.0761)	(0.0751)	(0.0760)
Months*Lv3	-0.324***	-0.352***	-0.324***	-0.329***
	(0.0743)	(0.0719)	(0.0743)	(0.0729)
Months*Rec	-0.158*	-1.223***	-0.158*	-0.0733
	(0.0929)	(0.195)	(0.0929)	(0.0883)
Months*Rec*RA		1.210***		
		(0.216)		
Observations	1,440	1,440	1,440	1,350
Number of ID	30	30	30	30
Controls	X	X	X	X

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: DD Estimation: DVI (outlier) excluded from observations.

Dependent Variable: Log Rate of Assaults

VARIABLES	(1) Base	(2) Controls	(3) TimeFE	(4) 3mo.Gap
TreatLv2*Post	-0.537***	-0.405***	-0.406***	-0.459***
	(0.176)	(0.144)	(0.123)	(0.165)
TreatLv3*Post	-0.304	-0.217	-0.211	-0.307
	(0.278)	(0.267)	(0.145)	(0.307)
TreatRec*Post	0.241	0.277	0.207	0.398***
	(0.187)	(0.176)	(0.180)	(0.0993)
Observations	1,421	1,421	1,421	1,334
Controls	None	X	X	X
Trend/Gap	No	No	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: DD Model Placebo Tests

Dep. Variable: Log Rate of the given form of misconduct.

VARIABLES	(1) Assaults	(2) Incidents	(3) Drugs	(4) Cellphone
TreatLv2*Post	-0.314**	-0.175	-0.162	-0.210
	(0.156)	(0.143)	(0.178)	(0.242)
TreatLv3*Post	-0.233	-0.0917	0.00244	0.197
	(0.175)	(0.160)	(0.200)	(0.273)
TreatRec*Post	0.0585	-0.0689	-0.550**	-0.0891
	(0.204)	(0.187)	(0.233)	(0.320)
Observations	780	780	780	779
Controls	X	X	X	X
Trend/Gap	No	No	No	No

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: IV Model: Murder and attempted murder included in outcome variable

Dep. Variable: Log Rate of Violence per 100 inmates

VARIABLES	(1) Base IV	(2) Interact RA	(3) Exclusion	(4) Drop 3mo.
Crowding (P/K)	2.208***	1.656***	1.911**	2.338***
	(0.604)	(0.481)	(0.755)	(0.605)
Observations	1,440	1,440	1,440	1,350
Number of ID	30	30	30	30
Controls	X	X	X+Months	X
Exclusions	Basic	Months*S*RA	Months*S	Base
F test IVs	10.34	26.81	10.05	10.59

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: IV Model: Staff assaults excluded from outcome variable

Dep. Variable: Log Rate of Inmate-on-inmate Assault

	(1)	(2)	(3)	(4)
VARIABLES	Base IV	Interact RA	Exclusion	Drop 3mo.
Crowding (P/K)	1.763**	1.123*	1.521*	1.958***
	(0.752)	(0.605)	(0.872)	(0.744)
Observations	1,440	1,440	1,440	1,350
Number of ID	30	30	30	30
Controls	X	X	X+Months	X
Exclusions	Basic	Months*S*RA	Months*S	Base
F test IVs	10.34	26.81	10.05	10.59

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

13 includes murder and attempted murder with the original measures of assault and battery. This leads to slightly larger point estimates, but no substantive changes in outcomes. Table 14 excludes assaults on staff members from the outcome variable and finds diminished statistical significance and point estimates in each specification. This suggests that variation in the rate of aggression towards staff is a dimension in which crowding impacts violence.

The effects of the reception adjustment on alternate subpopulations is illustrated in Figures 10 through 13. Although there is some time variation following AB 109 for each of these, none of them follow the distinct pattern shown for the security level 3 population.

Figure 14 shows the change in several measures of misconduct, measured over the 6 months preceding implementation of AB 109 and the 4th through 9th months following it. This table provides context for the decision to focus on misconduct measured via rates of assault. The other forms of misconduct are generally less stable and subject to more uncertain sources of variation.

Figure 15 shows changes in the participation rate (per 100 inmates) in the programs included in the standard set of controls. For these some increases are expected since population is decreasing and there is no reason to expect a decrease in program capacities. The two most notable things in this figure are the decrease in academic enrollment and the large increase in SATF participation at reception facilities. The change in academic enrollment, if significant at all, is likely due to some statewide institutional change (such as a reduction in education funding) since it is relatively

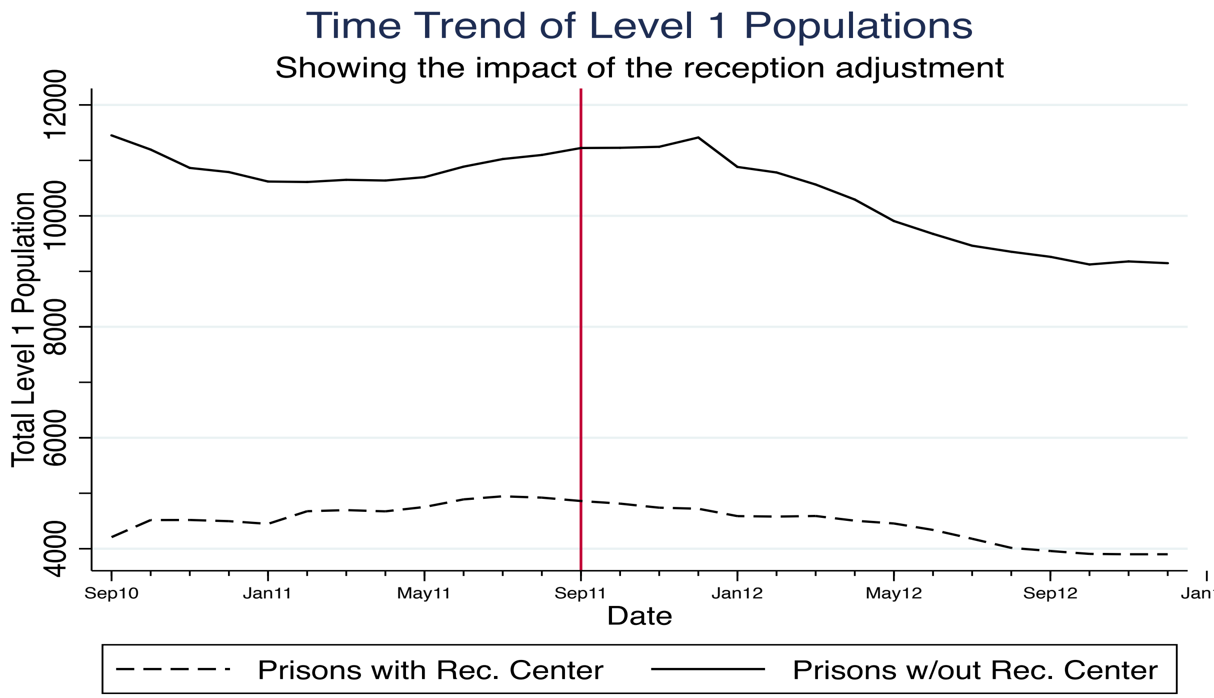

Figure 10: *This figure shows the impact of the reception adjustment on the level 1 subpopulation. The time trends are for sum of security level 1 populations parsed by whether the prison has a reception center facility or not. The vertical line denotes the last observation prior to implementation of AB 109.*

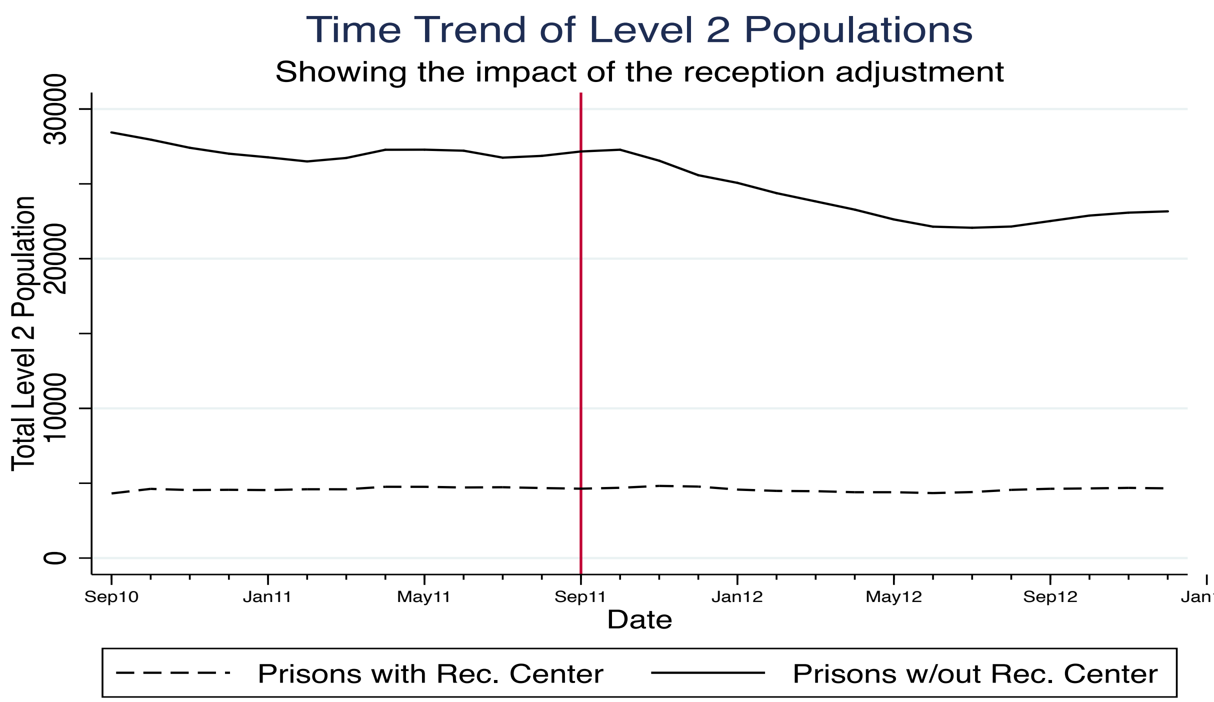

Figure 11: *This figure shows the impact of the reception adjustment on the level 2 subpopulation. The time trends are for sum of security level 2 populations parsed by whether the prison has a reception center facility or not. Note that the effect of RA is conflated with that of AB 109 for this subpopulation. The vertical line denotes the last observation prior to implementation of AB 109.*

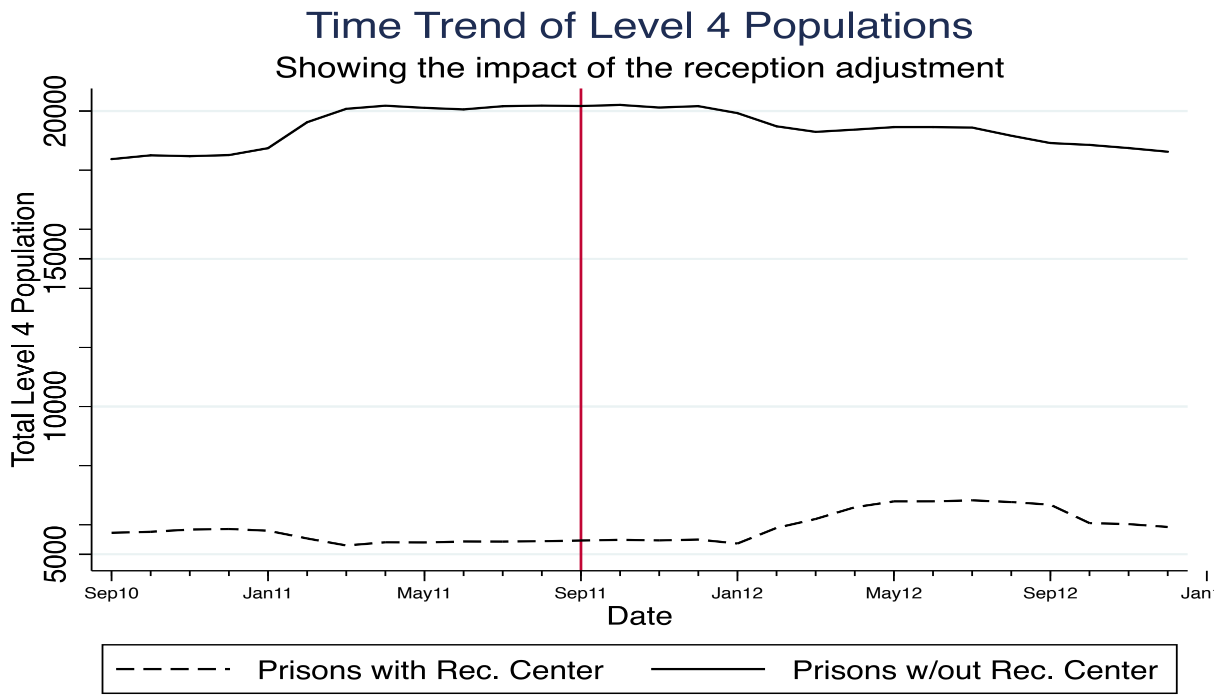

Figure 12: *This figure shows the impact of the reception adjustment on the level 4 subpopulation. The time trends are for sum of security level 4 populations parsed by whether the prison has a reception center facility or not. The vertical line denotes the last observation prior to implementation of AB 109.*

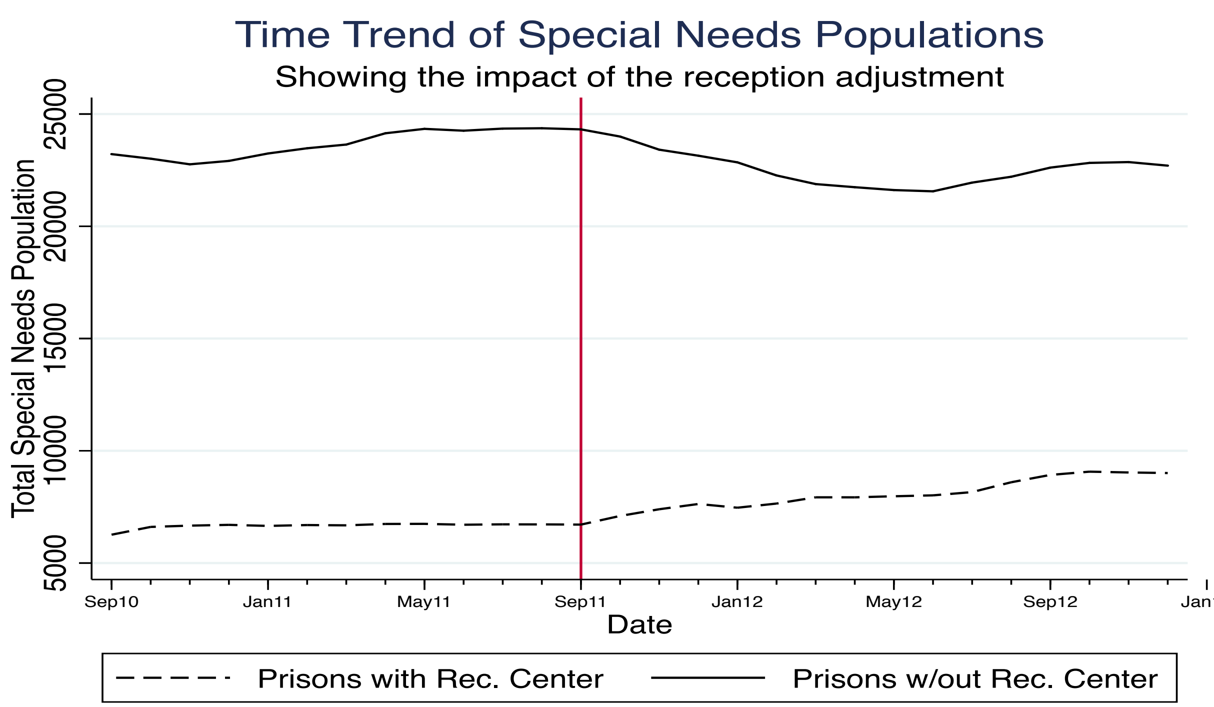

Figure 13: *This figure shows the impact of the reception adjustment on the special needs subpopulation. The time trends are for sum of special needs populations parsed by whether the prison has a reception center facility or not. The vertical line denotes the last observation prior to implementation of AB 109.*

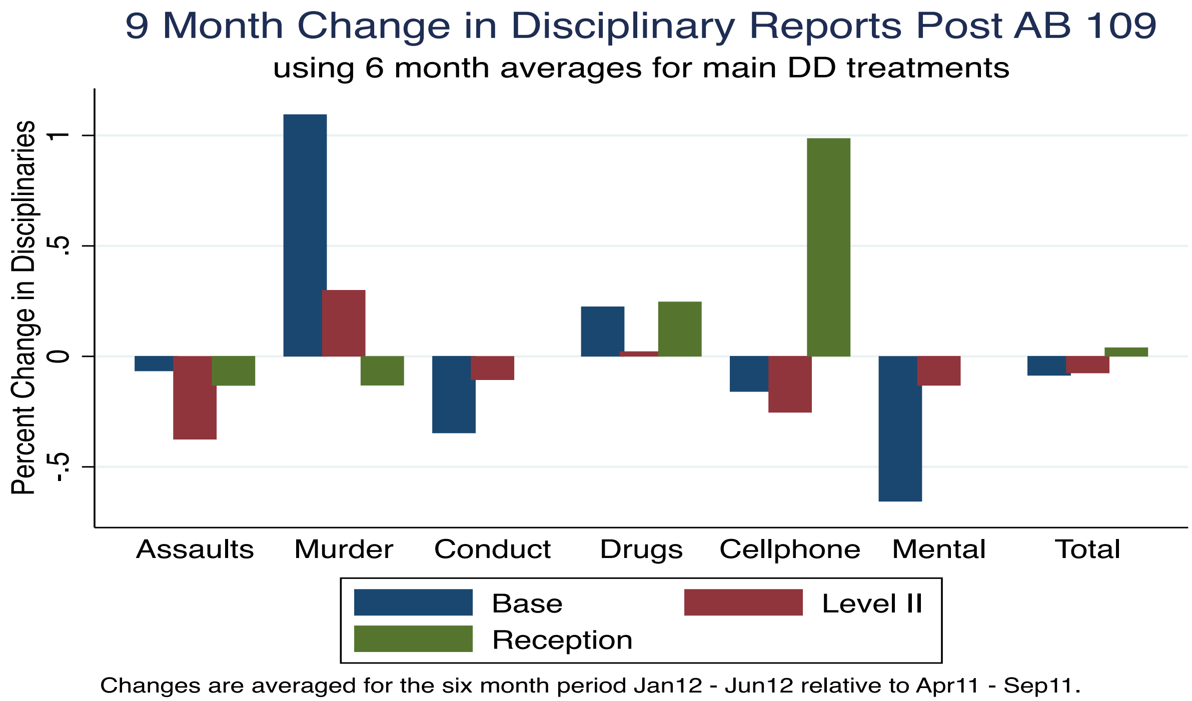

Figure 14: *This figure shows changes in the rate (per 100 inmates) of several types of disciplinaries. The changes are in the six month average measured from January 2012 through June 2012, relative to the average just prior to implementation of AB 109, April 2011 through September 2011. Source: Generated from CDCR CompStat reporting data.*

uniform across the three types of prisons. The increase in SATF beds can be partially explained by the population decrease, but could imply increased demand for substance abuse treatment since the waitlist for the program increases quite a bit as well[33].

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[33]The curious null effect for both SATF categories in the 'Others' group of prisons is due to the fact that all Substance Abuse Treatment facilities are in prisons with a reception center or high proportion of security level II inmates.

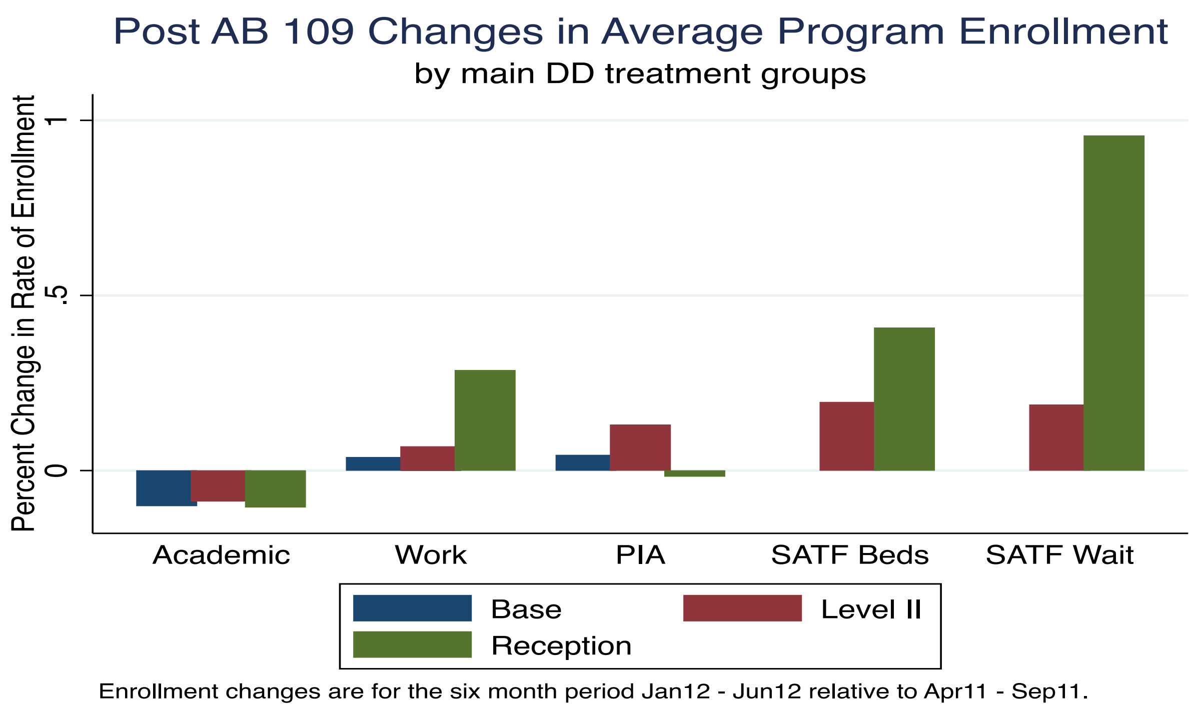

Figure 15: *This figure shows changes in the rate (per 100 inmates) of several types of program enrollment. The changes are in the six month average measured from January 2012 through June 2012, relative to average just prior to implementation of AB 109, April 2011 through September 2011. Source: Generated from CDCR CompStat reporting data.*