# Locked up and awaiting trial: A natural experiment testing the criminogenic and punitive effects of spending a week or more in pretrial detention

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**Abstract**

This study provides a rigorous assessment of the public safety outcomes of pretrial detention by estimating the criminogenic and punitive effects of spending at least one week in pretrial detention across three jail systems in two states. Jails are a unique criminal justice contact point because they hold individuals at different stages of case processing, including individuals awaiting trial, and those serving shorter sentences or waiting to be transferred to prison. Pretrial incarceration is arguably one of the most consequential decisions in case processing for an individual. A small body of research has emerged to show that pretrial detention is both criminogenic (i.e., leads to higher arrest rates) and punitive (i.e., leads to higher conviction rates). In this paper, we use a doubly robust difference-in-differences design to assess the relationship between pretrial detention with court appearances, new arrests prior to adjudication, and convictions for the instant offense. The findings of this research study provide strong evidence that pretrial detention leads to increased likelihood that individuals will miss court and be arrested for new crimes.

## Introduction

Judges routinely decide whether to release someone and set bail amounts for release after someone has been admitted to a jail. While these decisions may consider public safety, the choice to detain someone can have very significant consequences for detained individuals. For example, research indicates that the experience of pretrial detention is associated with a greater chance of being convicted and receiving a longer sentence. Scholarship suggests that detention can destabilize people such that they have higher post-adjudication recidivism rates (Dobbie, Golden, and Yang, 2018; Sacks and Ackerman, 2014). Recent ethnographic accounts further insinuate that pretrial detention may interfere with one's life chances, enforce racial divisions, and strain family relationships (Walker, 2022). Although individuals incarcerated prior to trial are unconvicted, some are confined in jail for weeks, months, or even years prior to their adjudication (Lowenkamp, 2022). The application of pretrial detention is complicated by the fact that judges can consider extralegal factors such as one's employment status and community ties in their decision-making (Goldkamp and Vilcica, 2009) and often rely on financial conditions (or bail) as a release requirement. Despite the high stakes, the empirical research on the public safety effects of pretrial detention to increase scheduled court appearances and reduce new crimes prior to adjudication remains scant.

Scholarship examining the average treatment effects of time spent in pretrial detention is critical for at least three reasons. First, prior research has largely focused on the causes and consequences of prison incarceration rather than jail detention (Nagin, 2013; Petrich, Pratt, Jonson, and Cullen, 2021). Jails, however, differ considerably from prisons in terms of their administration, population, and operation (Newport, 2023; Walker, 2022). It remains unknown, therefore, whether these two carceral settings may produce similar (or different) impacts among their inhabitants.

Second, jails are an important yet understudied part of mass incarceration with nearly seven million admissions into local jails each year (Zeng, 2022). Jails are where mass incarceration begins, as most people held in jails have yet to be convicted, and nearly every person in prison was detained in a jail. A better understanding of jails and their impacts are critical for the development of strategies that can help reduce the size of our nation's incarcerated population.

Third, incarcerating someone prior to their trial is arguably one of the most consequential decisions in case processing for an individual (Schlesinger, 2005). Surveys and interviews reveal that respondent's view pretrial detention as more uncertain, hectic, and painful than serving prison time (May, Applegate, Ruddell, and Wood, 2014). Given these realities, it is imperative that research assess what impacts time spent in pretrial detention holds on key public safety outcomes to provide judges with more information to base their pretrial detention decisions.

To address the gap in the literature, this study provides a rigorous assessment of the public safety benefits of pretrial detention by estimating the criminogenic and punitive effects of pretrial detention across three jail systems in two states. The analyses test the extent to which pretrial detention is associated with reductions in missed court appearances and arrests for new crimes during pretrial. More specifically, we apply a doubly robust difference-in-differences (DiD) estimator to calculate the average treatment effect of being detained for 7 days or more during pretrial compared to being admitted and released from jail within 1-day.

**Incarceration: Prisons and Jails**

Prisons are large institutions operated at the state or federal level that are responsible for incarcerating people for long periods. There are approximately 1,800 adult state and federal prisons that house about 1,200,000 adults, at yearend 2021 (Carson, 2022: 6). In contrast, jails are local institutions that are led by elected local legal actors that make decisions about how long and under what conditions people are detained in jail. These legal actors include mayors, jail administrators, sheriffs, prosecutors, and judges. There are approximately 2,900 jails that confine 636,300 adults, with 451,400 individuals held pretrial, in 2021 (Zeng, 2022: 7, 11).

Jails are local institutions that are used for an assortment of activities that include briefly detaining people after arrest, holding people that are awaiting a transfer to prison, detaining people as they await their bond hearing, detaining sentenced individuals, and even detaining people for a fee for the federal government (i.e., contract beds) (Turney and Conner, 2019). Since jails tend to detain individuals for shorter durations, they rarely offer services for substance abuse or mental health illnesses, and they have a high level of population turnover resulting in a less stable environment (May et al. 2014, Schnittker et al. 2012, Sugie and Turney 2017; Turney and Conner 2019). The negative effects of jails, however, are often discussed for their potential to act as a 'school for crime,' disrupt pro-social bonds, severe ties to legitimate employment and education, and foster anti-social attitudes and norms. Each of these factors separately and collectively may have different effects when compared to the experience of postconviction incarceration (Loefler and Nagin, 2022).

Jails are significant actors in local racial politics, and they play a major role in case processing the poor mostly through pretrial detention due to an inability to pay money bail (Baughman, 2018; Newport, 2023). The moral debates about the use of jail incarceration are nearly synonymous with pretrial detention and one's inability to pay bail, which has been shown to disproportionately impact the poor and people of color (Ares, Rankin, and Sturz, 1963; Foote, 1954; Schlesinger, 2005). Nevertheless, proponents argue that pretrial detention and bail reduce the prevalence of missed court hearings and new crimes while someone is out on pretrial release (Helland and Tabarrok, 2004). A small body of research, however, suggests that pretrial detention is both criminogenic (i.e., leads to higher re-arrest rates) and punitive (i.e., leads to more convictions for current charges) (Lowenkamp, 2022; Phillips, 2007; 2008). The study of jails has laid somewhat dormant for several decades as prisons became the central focus of attention during the era of mass incarceration (Garland, 2001).

Across the different types of jail confinement, the use of pretrial detention is often characterized as producing a particularly high level of uncertainty and anticipatory stress about one's future and that may have direct negative effect to worsen mental health (Sugie and Turney, 2017). Pretrial populations are a large and growing contributor of mass incarceration. Although more people are incarcerated (for longer periods) in prisons than jails, there were 6,900,000 admissions to jails (Zeng, 2022) compared to about 420,000 admissions to prisons in 2021 (Carson, 2022). According to the Bureau of Justice Statistics (BJS), the proportion of jail populations that are unconvicted has increased from 50% in 1985 to nearly 69% in 2021 (Zeng, 2022). BJS estimated that nearly 95% of the growth in jail populations since 2000 was a result of the increase in the proportion of those held in jails that are unconvicted (Minton and Zeng, 2015). During pretrial, individuals have not been convicted of a crime and can be released to the community while they await trial, but many jails are filled with pretrial populations because judges can deny pretrial release and others are detained because they cannot afford bail. Despite the goal of pretrial incarceration to improve public safety outcomes, it remains an open empirical question whether detention leads to increased court appearances and fewer crimes.

## Incarceration and Crime Prevention

Incarceration is supported by some as necessary to prevent future crime through incapacitation and deterrence (Von Hirsch et al., 2009). Research is mixed on the ability of prison incarceration to decrease crime (Sweet and Apel, 2007), with longer prison stays related to weakened life chances (Sampson and Laub, 1993). Although our study is focused on the effects of jail incarceration, we briefly review the findings related to prison incarceration and crime prevention. A central purpose of incarceration is to prevent future criminality through incapacitation of crime prone individuals, and general and specific deterrence by communicating the consequences of crime with the possibility for punishment (Apel, 2022). Initially, research on the deterrent effects of prison sentences focused on how individuals perceive the severity and certainty of punishments (Waldo and Chiricos, 1972). If incarceration is to have a deterrent effect, people need to understand and perceive the punishments as important and something to be avoided (Apel, 2022). There is, however, a recognition that policies need to balance the crime prevention effects of incarceration – through incapacitation and deterrence – with the potential for creating a criminogenic effect through the experience of and collateral consequences of punishment.

The deterrence research has shown heterogeneous findings with effects ranging from null to very large effects (Nagin, 2013). There is little evidence that increasing already long prison sentences has more than a marginal deterrent effect. Prior research has found negative statistically significant results between crime prevention and incarceration (Donahue, 2007). There is support for using imprisonment to enforce fine payment (Weisburd, Einat, and Kowalski, 2008), a deterrent effect for California's three-strike laws (Helland and Tabarrok, 2007), and null findings for sentence enhancements for gun crimes (Raphael and Ludwig, 2003).

In Nagin's (2013) review of the deterrent effects of punishment, he pointed out that the strongest support is for the certainty of punishment. More recently, Loeffler and Nagin (2022) provided a review of studies testing the crime prevention effects of incarceration that use more sophisticated methods (e.g., instrumental variable designs) capable of controlling for unobservable heterogeneity. These more rigorous studies found mostly null findings for imprisonment to reduce recidivism using instrumental variable and regression discontinuity designs. Interestingly, the authors concluded that "none find evidence of a crime-reduction effect" (Loeffler and Nagin, 2022: 140).

**Effects of Pretrial Detention**

Jails are an unfortunate yet needed aspect of contemporary societies. Responding to criminal behavior and protecting the public are important social functions. Jails are a unique criminal justice contact point because they hold individuals at different stages of case processing, including those serving sentences shorter than one year or waiting to be transferred to prison. Most people in jail, however, are incarcerated awaiting trial because they cannot afford the required bail as less than five percent of individuals are denied release (Reaves, 2013).

The current study advances prior research finding a correlation between pretrial detention and conviction and recidivism (Lowenkamp, 2022; Phillips, 2007; 2008). Pretrial release and bail decisions take place shortly after a defendant's arrest when a magistrate, judge, or other judicial officer establishes the conditions of release to motivate a defendant's appearance in court and reduce the chances of new crimes during pretrial release (DeMichele, Comfort et al., 2021). The pretrial detention decision is associated with personal wellbeing (e.g., family cohesion, employment) and legal system outcomes (e.g., conviction, rearrest) (Sacks and Ackerman, 2014).

The empirical challenge for testing the association of pretrial detention on legal system outcomes is that the people who are detained and those who are released tend to be different in important ways. It could be that judges apply pretrial detention to sort individuals based on differences in their probability of recidivism. Detained individuals tend to have more serious and lengthier criminal histories, and they may vary on characteristics such as wealth, community ties, or lawyer quality. Pretrial detention can affect an individual's ability to prepare for a case or willingness to go to trial. Prior research on the relationship between time spent in pretrial detention with missed court appearances and arrests for new crimes is mixed, but there are more consistent findings of a punitive effect of pretrial detention (e.g., conviction, sentence severity).

In the 1960s, the Manhattan Bail Project (Ares et al., 1961) showed that judges could reduce disparities, increase the released population, and maintain appearance rates. The Manhattan Bail Project was an innovative study that made significant contributions to the field because this study was an initial attempt to measure the impact of pretrial detention on individual outcomes and sentencing outcomes. The authors found that the detained were more likely to be convicted and sentenced to incarceration. Although the Manhattan study marks the beginning of modern research on pretrial detention, there are important methodological weaknesses that makes it difficult to identify any causal impact of pretrial detention (Heaton, Mayson, and Stevenson, 2017).

Prior research consistently found that pretrial detention is associated with more punitive outcomes. In an early study, Goldkamp (1980) found that 39% of defendants released within twenty-four hours had their cases diverted out of the criminal justice system. More stark differences by detention status appeared at sentencing. Almost 20% of those detained pretrial were sentenced to prison for two years or more compared to just 1% of those released in the community before trial. More recently, researchers demonstrated the cumulative disadvantages related to case processing characteristics. About 40% of the Black-White disparity in sentences to incarceration was attributed to racial differences in having hired private counsel, pretrial detention, and criminal history (Wooldredge, Frank, Goulette, and Travis, 2015).

A growing body of research underscored how the experience of pretrial detention produces more guilty pleas, higher rates of conviction, and harsher sentences. Prior research suggests there are likely both costs and benefits to pretrial detention because some have found that detained individuals are more likely to plead guilty (Gupta, Hansman, and Frenchman, 2016; Stevenson and Mayson, 2017), whereas others have found that pretrial detention may have no effect on new crimes and missed court appearances (Dobbie et al., 2018), others have found pretrial detention associated with new crimes (Lowenkamp, 2022). More recently, there have been a handful of studies using more rigorous quasi-experimental methods to test the effects of pretrial detention.

Researchers have addressed endogeneity by leveraging the random assignment of cases to judges at pretrial given the natural tendencies of judges to vary in their leniency when it comes to setting bail amounts (i.e., some judges tend to set higher or lower bail amounts on average). In Philadelphia and Pittsburgh, Gupta et al. (2016) used a large sample of criminal cases to analyze the consequences of money bail to isolate the causal effect of pretrial detention by exploiting variation in bail-setting tendencies among judges. The results showed the use of pretrial detention was associated with a 12-point increase in the likelihood of conviction and a 6–9 percent increase in recidivism post-adjudication.

The effects of pretrial detention are especially important for individuals charged with misdemeanors because these individuals tend to face short sentences – typically, time served – or probation (Feeley, 1979). Using a natural experiment to assess the causal effects of pretrial detention for misdemeanants in Harris County, Texas, Heaton et al. (2017) found that individuals detained pretrial, on average, were 43% more likely to be sentenced to jail, 25% more likely to plead guilty, and the detained were more likely to receive a sentence that was, on average, nine days longer. Besides the punitive effects of pretrial detention, Heaton et al. (2017) found that pretrial detention had a brief incapacitation effect that reversed by eighteen months after their initial bail hearing. Pretrial detention was associated with a 30% increase in new felony charges and a 20% increase in new misdemeanor charges, leading Heaton et al. (2017: 718) to conclude that "even short-term detention has criminogenic effects."

Pretrial detention may increase future crime following release through two primary mechanisms. First, pretrial detention may increase crime if pretrial detention is criminogenic because of harsh conditions and negative peer influences (e.g., Chen and Shapiro 2007, Bayer, Hjalmarsson, and Pozen 2009). Second, pretrial detention may increase rearrest through an increased likelihood of unemployment and general detachment of prosocial institutions. Although prior research is consistent in finding a positive association with conviction and pretrial detention, there is more variation in the association of pretrial detention on missed court appearances and new arrests. Recently, several studies have found a potential incapacitation effect of pretrial detention that wanes and results in a criminogenic amplification effect (e.g., Heaton et al., 2017; Leslie and Pope, 2017). In a recent research review, Loeffler and Nagin (2022: 143) summarized the research to state that "pretrial detention exacerbates post-release recidivism. With the combination of disruption from temporary detention and the absence of programming or reentry resources, pretrial detention appears unfavorable compared to less restrictive pretrial monitoring alternatives."

In Walker's ethnographic account of jail incarceration, he detailed the cumulative effects associated with jail incarceration that are rooted in the uncertainty about the process, not knowing how long one will be incarcerated, and the stress associated with meeting familial responsibilities (e.g., childcare). Walker's account detailed a growing sense of "humiliation, guilt, regrets, and wretchedness" (2022: 7) in which he described horrible conditions due to crowding and hostile behaviors (mostly from officers) that unfolded with even a brief time spent in pretrial detention.

In the current study, we measure initial pretrial release based on whether an individual is released within more than 7 days of their booking for three reasons. First, prior researchers have used different detention cutoffs when studying the association between time spent in pretrial and convictions and recidivism. For instance, Dobbie et al. (2018) compared a released group with those detained more than three days post-arraignment, and Heaton et al. (2017) used a group detained seven days following a bail hearing. In another study, Lowenkamp (2022) used timestamp data in a series of logistic models with 0-23 hours as the reference group and found just more than one day to have negative effects on rearrest rates (but not missed court appearances). Second, we conducted several sets of analyses that included developing comparison groups with different detention cutoffs of more than 1 day and more than 3 days spent in pretrial detention. Due to space limitations, we report the findings from the more than 7 days in pretrial detention group, but the other time specific detention groups yielded similar results.[1] Third, we follow Smith's (2022) qualitative research in which she showed the effects (e.g., material losses, diminished emotional and psychological well-being) of the first week spent

[1] Due to interest in the effects of time spent in pretrial detention on legal system outcomes, the analyses were replicated using individuals that served more than 1 day in pretrial detention (N = 20,825) and individuals that served more than 3 days in pretrial detention (N = 8,646) as the treatment groups. The findings were substantively similar to those found for more than 7 days in pretrial detention and can be provided upon request.

in pretrial detention. For these reasons, we are interested to understand the causal effects of being detained in jail at least one week.

**The Current Study**

Natural experiments are a powerful technique to assess treatment effects when true randomized experiments are not possible. Further, natural experiments are a widely accepted technique for assessing policy effects. In the current context, one needs to do more than compare pre- and post-treatment outcomes for individuals detained because the results are likely contaminated by temporal trends, events, and other issues between the pre- and post-treatment periods. For the current study, judge decisions[2] provide an approximation of a natural experiment because they are making detention decisions based on policies used to assess the legal parameters around anyone's ability to be detained pretrial. This approach provides an advancement over other studies relying on as-good-as-random assignment leveraging random judge assignment (Dobbie et al., 2018). The difference-in-differences estimator is based on the notion that for policy studies people are sorted into relatively naturally occurring groups such that some people are naturally exposed to the treatment and others are not, which creates an untreated comparison group. This approach was launched in several well-known economic studies (e.g., Ashenfelter, 1978; Card and Krueger, 1994), but the traditional difference-in-differences framework is difficult to use in real-world settings due to endogeneity assumptions.

We build on multiple research trends in the econometrics literature to frame the current evaluation as a missing data problem to assess potential outcomes (Rubin, 1974; Heckman et al., 1997). For the current study, $Y^0(i)$ represents the outcome (e.g., missed court, new arrests) that individual *i* would have if they were detained for 1 day or less (i.e., absence of the treatment).

[2] Judge decisions are not merely a binary of release or detain. Rather, judges may set financial conditions of release in the form of a bail payment that exceeds what individual either can afford or are willing to pay.

Similarly, $Y^1(i)$ represents the outcome that individual *i* would have if they were detained for 7 days or longer (i.e., exposed to the treatment). The effect of pretrial detention (i.e., treatment) on the outcome (e.g., missed court, new arrests) for individual *i* is then naturally defined as $Y^1(i) - Y^0(i)$. The evaluation challenge is that for any individual *i* we cannot observe the same person in both conditions $Y^0(i)$ and $Y^1(i)$, hence, we are unable to estimate the average treatment effect $Y^1(i) - Y^0(i)$ without establishing a counterfactual condition emulating the treatment condition.

The DiD estimator comes with strong assumptions, but most notably the DiD estimator "requires that in absence of the treatment, the average outcomes for the treated and controls would have followed parallel paths over time" (Abadie, 2005: 2). The parallel trends assumption is implausible in many real-world settings because people are sorted into groups based upon individual level pre-treatment characteristics that are associated with the outcomes. This assumption states that the average outcomes for the treated and control groups would have followed parallel trends in the absence of the treatment (Equation 1).

**[Equation 1]**

$$E[Y^1(\mathrm{i}) - Y^0(\mathrm{i})|X, D = 1] = E[Y^1(1) - Y^0(0)|X, D = 0].$$

The DiD framework assesses the relative differences in the pre- and post-treatment outcomes of the detained (treatment group) and the released (comparison group). For the DiD estimator to support causal interpretation, one must satisfy the parallel trends assumption to ensure that the assessed differences are due to the treatment. Unfortunately, no statistical tests exist to examine if the parallel trends assumption is violated, but evidence of a violation can be developed by assigning balance or imbalance in the covariates associated with outcomes across the treatment and control groups. This is true for the current study as we found judges sort individuals into released and detained groups varied by prior criminal history and seriousness of current and past known criminal activity. These differences in pre-treatment characteristics between the released and detained creates empirical challenges to disentangle the average treatment effects of those detained. Fortunately, however, violations of the parallel trend assumption can be limited with a two-step strategy (Robins et al., 1994).

Typically, researchers include pre-treatment covariates in an outcome regression model and assume the parallel trends assumption is satisfied. This, however, often is not the case. To address the parallel trends assumption, we apply recent advancements in the causal inference literature. Sant'Anna and Zhao (2020) demonstrated how to bring together two strands of causal inference literature by merging the work of Heckman et al. (1998) on DiD outcome regression estimators and Abadie's work on (2005) inverse probability weighted (IPW) estimators within a DiD framework. These literatures on DiD estimators are blended with the doubly robust estimator's literature (Robins et al., 1994; Wooldridge, 2007). We follow Sant'Anna and Zhao (2020) to bypass choosing between the outcome regression or the inverse probability weighting approaches by combining them to form doubly robust (DR) estimator for the average treatment effect of the detained. In this sense, double robustness indicates that the resulting odds ratios estimate the average treatment effect for the detained even if either (but not both) the logistic regression or the inverse probability weight model are misspecified.

The doubly robust DiD estimator for the average treatment effects for the detained is designed to leverage the strengths of each DiD method (i.e., regression, propensity weights) and avoid some of their limitations. On an intuitive level, we assume that the inverse probability weight represents the probability of an individual being included in the treated group. This works by down-weighting the distribution of $Y^1(i) – Y^0(i)$ for the untreated (D=0) for the values of the covariates ($X_i$) that are under-represented among the untreated (i.e., individuals with low

P(D=1|X)/P(D=0|X)), and up-weighting $Y^1(i) – Y^0(i)$ for those values of the covariates under-represented among the untreated (i.e., those with high P(D =1|X)/P(D=0|X)).

Imbens and Wooldridge (2008) pointed out that propensity weighting within the DiD framework removes the bias from omitted right hand side covariates in the regression. They go further to describe "the idea behind the doubly-robust estimators…can be interpreted as removing the correlation between $D_i$ and $X_i$, and regression as removing the direct effect of $X_i$" (Imbens and Wooldridge, 2008: 34). Thus, combining regression and weighting has the potential added robustness by removing the correlation between the omitted covariates, and reducing the correlation between the omitted and included variables.

**Research Questions - Estimate Average Treatment Effects for the Detained**

The current study is motivated by wanting to estimate the effect of being detained in jail prior to trial. More specifically, we test the criminogenic and punitive effects of pretrial detention with four dependent variables to understand the different dimensions of concern for legal system outcomes. Judges and prosecutors are tasked (often elected) to maintain public safety and enforce the law and they need to ensure that people return to court for all their hearings. In most US jurisdictions, people are afforded an opportunity at release within 24-48 hours after their jail admission. However, there can be multiple court appearances required to complete the adjudication of the case. For this reason, legal actors (in most jurisdictions) can detain individuals for concerns that someone will fail to appear (FTA) in court for subsequent hearings. There is no doubt that it is important for people to attend all court hearings, but, taking a social cost perspective, this is not the most pressing issue facing court systems. Simply, people may miss court for a host of reasons that can include forgetting, other responsibilities (e.g., childcare), fear of prosecution, and willfully fleeing.

Another major issue driving legal actor pretrial decision making is concern of released individuals committing new crimes while they are in the community. Legal actor's base decisions on their perceptions of riskiness of whether an individual if released will go on to be arrested for a new crime. With that said, however, not all crimes are equal. That is, legal actors and the public are most concerned with the commission of serious and violent crimes that cause harm to individuals. Although new violent crimes are rare during pretrial, they do occur and the concern of future violent crimes during pretrial drives decision makers.

Prior research suggests that pretrial detention has limited public safety benefits. We seek to answer the following research questions:

- R1: Does being detained for 7 days or more effect the likelihood of failing to appear when compared to individuals detained for 1 day or less?
- R2: Does being detained for 7 days or more effect the likelihood of criminal arrest when compared to individuals detained for 1 day or less?
- R3: Does being detained for 7 days or more effect the likelihood of violent criminal arrest when compared to individuals detained for 1 day or less?
- R4: Does being detained for 7 days or more effect the likelihood of conviction when compared to individuals detained for 1 day or less?

## 5. Methods

### *5.1. Sample*

The data for the current study were collected as part of a larger multi-county project researching pretrial systems. We worked with local and state officials in three counties (in two states) to develop pretrial datasets with adults admitted into jails between January 1, 2017, and December 31, 2018. It is worth noting that pretrial datasets do not exist, but rather need to be created by linking jail, court, and criminal history records. The current sample was limited to adults admitted to jail for a new crime with admissions associated with posttrial sentences, probation or parole violations, appeals, transfers, juveniles, and immigration detainers removed. The jail admission data were combined with criminal histories that allowed us to assess criminal activity prior to and after the charge for which someone was admitted to jail between 2017 and 2018. The analytic sample used in the current study was limited to the first booking for each unique individual who was released into the community during pretrial after serving 1 or fewer days in pretrial detention (N = 10,915) or more than 7 days in pretrial detention (N = 5,317).[3] Individuals were included in the study only once to avoid overfitting analysis on individuals cycling through jails more frequently.

### *5.2. Measures*

#### *5.2.1. Defining the Treatment and Control Groups*

A treatment condition was developed comparing individuals who were detained for more than 7 days to individuals who were detained 1 day or less during pretrial. The individuals detained 1 day or less represent a viable control group because they were exposed to the conditions of pretrial confinement for a short period. The individuals in the control group were released from the facility the same day or the subsequent calendar day and as such they were unlikely to lose a job, miss many family responsibilities, or adopt any criminogenic features associated with jail culture. For the most part, these are individuals admitted to jail on less serious offenses, they have minor or no prior criminal history records, and they may be detained until they become sober.

#### *5.2.2. Legal System Outcomes*

We are modeling the pre- and post-treatment probabilities of four legal system outcomes to assess the average treatment effects of pretrial detention. The four outcomes are: 1. failure to appear (FTA), 2. new criminal arrest (NCA), 3. new violent criminal arrest (NVCA), and 4.

[3] The individuals who served 7 or less days and more than 1 day in pretrial detention were removed from the analytical sample to ensure that the counterfactual for the group of individuals who served more than 7 days in pretrial detention was individuals who served 1 or fewer days in pretrial detention.

conviction status. To estimate the average treatment effect for the detained, we first need to model the entire criminal history of an individual prior to being exposed to pretrial detention for the current charge. We do this to develop a pre-detention baseline for each person in the sample (i.e., the pre-pretrial period). The post-detention observational period is the time between release from pretrial detention and the disposition associated with the current charge or December 31st, 2019 for those that are right censored.[4] The pre-treatment indicators of criminal activity are based on probabilities of convictions for any crime or a violent crime (respectively) prior to being detained for the current charge.[5] The post-treatment outcomes were operationalized to capture if an individual failed to appear in court, was arrested for a new crime or a new violent crime before disposition, or whether they were convicted for the current charges within the censoring time (i.e., December 31st, 2019).

*5.2.3. Pre-Post Pretrial Detention Indicator*

A dichotomous indicator was created to identify the pre- (=0) and post-detention periods (=1) to permit the estimation of the DiD models.

*5.2.5. Covariates of Interest*

Fifteen covariates were introduced into the analysis to adjust for potential sources of bias when estimating the association between pretrial detention and the four legal system outcomes (Lowenkamp et al., 2013). First, time at risk measured the number of days between being released from pretrial detention and an individual's disposition on the current charge or December 31st, 2019. Second, age at current arrest was the defendant's age when they were

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[4] Of the 16,232 individuals included in the analytical sample, 12% or 1,983 were right censored. Right censorship (i.e., sentence data was after 12/31/2019) was almost evenly split between defendants detained for more than 7 days (N = 1,019 or 51%) and defendants detained for 1 day or less (N = 964 or 49%).

[5] Due to limitations capturing the life-time arrest history of the defendants, the pre-detention operationalization of new criminal arrest and new violent criminal arrest were created using the life-time conviction history of the defendants. The pre-detention indicator for new criminal arrest and convicted are the same.

arrested for the current charge. Third, prior incarceration was a dichotomous indicator identifying if the defendant was incarcerated at any point during their life (0 = No; 1 = Yes). Fourth, pending charge indicated if the defendant had other pending charges when they were booked into jail for the current charge (0 = No; 1 = Yes). Fifth, the total number of charges captured the number of charges assigned to an individual at the time of booking. Sixth, misdemeanor identified if the highest degree for the current charges was a misdemeanor ("1") or a felony ("0") offense. Seventh, the offense type of the most serious charge was measured using four dichotomous indicators – other offense, property offense, public order offense, and violent offense – where the reference category was drug offense. Eight, the defendant's race was measured where "1" indicated that the defendant was white and "0" indicated that the defendant was a person of color.[6] Ninth, male was the biological sex of the defendant at the time of booking. Finally, the county of commitment was measured using two dichotomous indicators – County 2, County 3 – with County 1 serving as the reference category.

### *5.3. Analytic Strategy*

A five-step analytical strategy was produced to test the four hypotheses identified above. First, the analyses begin with reporting the descriptive statistics for the entire sample and the treatment and control groups. Second, the conditional probability (i.e., propensity score) of being detained for more than 7 days was calculated by regressing the treatment condition on 15 covariates using a fixed-effects binary logistic regression model (Guo and Fraser, 2014). Third, an Average Treatment Effect (ATE) Inverse Probability Weight (IPW) was calculated (Sant'Anna and Zhao, 2020). Fourth, four weighted fixed effects doubly robust DiD models were

[6] The full analysis was not limited to Black and White defendants. Nevertheless, due to the limited number of defendants of Asian, Native American, Alaskan, or Hispanic descent these groups were combined into a single category with Black defendants. As discussed in the analytical strategy, non-Black non-White defendants were removed from the analysis examining the heterogeneity in the effects of pretrial detention for Black and White defendants.

estimated (Sant'Anna and Zhao, 2020). These models were estimated where failure to appear (FTA), new criminal arrest (NCA), new violent criminal arrest (NVCA), and conviction status were regressed on the pre- and post-detention period indicator, the treatment group indicator, the interaction between the two indicators, and 15 covariates. Fifth, the results of the weighted fixed effects DiD models were used to estimate predicted probabilities, which were plotted to observe the difference between the expected probability of the legal system outcomes and the observed outcomes for the treatment group.

*5.3.1. A Doubly Robust Difference-in-Differences Model*

A doubly robust difference-in-differences (DiD) analysis is a quasi-experimental statistical approach designed to estimate the causal effects of a treatment on an outcome (Conley and Taber, 2011). To approximate a randomized controlled trial (RCT), IPW can be integrated into a DiD model – single robust DiD – to increase covariate balance between the treatment and control groups to limit the potential confounding effects of covariates causing variation in both the treatment and legal system outcomes (Cunningham, 2021). IPW works by limiting the observable differences between the treatment and control groups on key covariates that could confound the association of interest (e.g., age, sex, race) (Guo and Fraser, 2014). The bias caused by the confounding effects of key covariates is reduced by limiting the observable differences between the groups, as the control group is more likely to emulate a true counterfactual condition for the treatment group. In comparison to propensity score matching, IPW is the preferred method of increasing covariate balance as it does not limit the number of treatment or control cases in the analytical sample and cannot be biased by the introduction of a non-random matching techniques (Guo and Fraser, 2014). In addition to weighting the observations by individuals' scores on key covariates, a doubly robust DiD model introduces covariates into the model predicting the outcome of interest. The process of introducing the covariates into the outcome models statistically adjusts for any residual variance shared between a covariate, the treatment, and the outcome further limiting the potential effects of confounder bias on the association between the treatment and the outcome.

DiD models estimate causal effects by creating a counterfactual condition using a pre-post comparison between a group exposed to the treatment condition (i.e., treatment group) and a group not exposed to the treatment condition (i.e., control group; Cunningham, 2021). The pre-post comparison is conducted by: 1. measuring the outcome of interest before the treatment group is exposed to the treatment condition, 2. measuring the outcome of interest after the treatment group is exposed to the treatment condition, 3. calculating the change in the outcome of interest for the treatment group from pre-treatment to post treatment, and 4. calculating the difference between the change experienced by the treatment group and the change experienced by the control group (Cunningham, 2021).

IPW is the inverse of the probability of being exposed to a treatment condition calculated using a series of covariates (Guo and Fraser, 2014). The IPW was calculated by estimating the probability of a defendant being detained during pretrial for more than 7 days using Equation 2. Detained for more than 7 days was regressed on an m x n matrix of predictors ($X$) using a fixed effects binary logistic regression model. In a binary logistic regression model, the dichotomous treatment variable ($T$) was transformed into logged odds of being exposed to the treatment ($ln\left(\frac{T_i}{1-T_i}\right)$) prior to regressing the treatment variable on the covariates included in the model (see Appendix A for pre-post weighting balance and Appendix B for the results of the IPW model).

**[Equation 2]**

$$ln\left(\frac{T_i}{1-T_i}\right) = \beta_0 + \beta_1 County_2 + \beta_2 County_3 + \beta_c X_i + \varepsilon_i$$

After estimating the model, the probability of being exposed to pretrial detention for more than 7 days – $p(T)$ – was calculated as the weighted sum of the defendant's scores on the predictors (Guo and Fraser, 2014; Equation 3).

**[Equation 3]**

$$p(T_i) = \frac{\exp(\beta_0 + \beta_1 County_2 + \beta_2 County_3 + \beta X_i + \varepsilon_i)}{[1 + \exp(\beta_0 + \beta_1 County_2 + \beta_2 County_3 + \beta X_i + \varepsilon_i)]}$$

The predicted probabilities ($p(T_i)$) were then used to calculate ATE IPWs for the cases exposed to pretrial detention for more than 7 days (treatment) or pretrial detention for 1 day or less (control). The IPWs for the treatment cases were calculated as $\frac{1}{p(T_i)}$, while the IPWs for the control cases were calculated as $\frac{1}{1-p(T_i)}$ (Guo and Fraser, 2014). The IPW is then used to weight the observations for the treatment and control cases when estimating a DiD model (Guo and Fraser, 2014; Sant'Anna and Zhao, 2020). This weighting process is designed to increase the similarities between the treatment and control groups, permitting the estimation of the Average Treatment Effect (ATE). Evident by the descriptive statistics presented in Table 1, this IPW process was necessary as substantive differences existed between the treatment and control groups. The ATE is the difference between the change experienced by the treatment group and the change experienced by the control group on average (Cunningham, 2021).

While weighted descriptive statistics provide limited information about the effectiveness of the IPW, a balancing analysis can be conducted to illustrate the benefits of integrating IPWs into a traditional DiD model. This balancing analysis, provided in Table A1 of Appendix A provides the pre-weighting and post-weighting balance (mean difference) between those detained for 1 day or less and those detained for more than 7 days. Evident by the pre-weighting statistics, individuals detained for 1 day or less were more likely to be arrested for a misdemeanor offense, other offense, and public order offense, as well as be white when compared to those detained for more than 7 days. Moreover, substantial differences existed between those detained for 1 day or less and those detained for at least 7 days, evident by nine Cohen's D values over .40. Post-weighting, however, minimized these differences – no Cohen's D values over .40 – and commonly flipped the direction of the differences and providing balance between the groups.[7] This balancing analysis provides support for the implementation of the Doubly Robust DiD model, as the differences between the treatment and control group were minimized creating a counterfactual condition that emulates the treatment condition.

After calculating the inverse probability weights, four weighted fixed effects DiD models were estimated predicting failure to appear, new arrests, new violent arrests, and convictions status (Goodman-Bacon, 2021). These models regressed the legal system outcomes (represented as $Y_i$) on pretrial detention for more than 7 days ($T_i$), the pre-post indicator ($PrePost_i$), interaction between the pre-post indicator and pretrial detention for more than 7 days ($T_i * PrePost_i$), and an m *x* n matrix of covariates (Equation 4).

**[Equation 4]**

$$ln\left(\frac{Y_i}{1-Y_i}\right) = \beta_0 + \beta_1 T_i + \beta_2 PrePost_i + \beta_3 (T_i * PrePost_i) + \beta_4 County_2 + \beta_5 County_3 + \beta_c X_i + \varepsilon_i$$

By estimating the models in this manner, $\beta_1$ represents the mean difference between individuals detained for 1 day or less and individuals detained for more than 7 days on the outcomes during the pre-period (Donald and Lang, 2007). $\beta_2$ represents the change in the outcome from the pre-detention to the post-detention observational period for both groups, while $\beta_3$ represents the difference in the change on the outcome from the pre-detention to the post-

[7] The magnitude of Cohen's D can be interpreted as indicative of negligible differences when below .2, small differences when between .21 and .50, moderate differences when between .51 and .80, and large differences when greater than .81 (Lakens, 2013).

detention periods between individuals detained for 1 day or less and individuals detained for more than 7 days (Donald and Lang, 2007). That is, $\beta_3$ represents the ATE of being detained for more than 7 days on the legal system outcomes (Athey and Imbens, 2006). $\beta_4$ and $\beta_5$ represent the county fixed effects estimates, while $\beta_c$ represents an *m* vector of slope coefficients for the *m* x *n* matrix of covariates included in the model. After estimating the weighted fixed effects DiD models, the probabilities of experiencing each outcome pre-detention and post-detention were plotted for those detained for more than 7 days and those detained for 1 day or less.[8]

## 6. Results

### *6.1. Descriptive Statistics*

Table 1 presents the descriptive statistics for the total sample, individuals detained for 1 day or less, and individuals detained for 7 days or more. Evident by the results, individuals detained for 7 days or more had higher rates of lifetime failure to appear, criminal convictions, and violent criminal convictions when compared to the individuals detained for 1 day or less. Moreover, their current offense was more likely to be a felony and violent when compared to individuals detained for 1 day or less. Corresponding with these differences in criminal history, individuals detained for 7 days or more had a higher rate of failure to appear, being convicted for the current charge, experiencing a new criminal arrest, and experiencing a new violent criminal arrest when compared to individuals detained for 1 day or less. Corresponding with the observable differences between the groups, it is likely that the DiD model would have violated

[8] As a sensitivity analysis, this process was replicated for the Male subsample, Female subsample, subsample of white individuals, and subsample of black individuals. The full model results and plotted probabilities are provided in Tables C1-C4 and Figures C1-C4 in Appendix C. To further supplement the primary analyses, the analytic strategy was replicated to compare individuals detained for more than 1 day and detained for at least 3 days to individuals detained for 1 day or less. The results of these model provided support for the conclusions drawn from the primary analyses. The full model results for these replications can be provided upon request.

the parallel trends assumption without integrating IPW into the estimation procedure (post-weighting balancing statistics are provided in Table A1 in Appendix A).

**Insert Table 1 About Here**

*6.2. Overall Sample*

**Insert Figure 1 and Table 2 About Here**

Figure 1 provides the predicted change from the pre-detention to the post-detention periods for those detained 7 days or more (dashed black line), those detained 1 day or less (solid black line), and the expected change for those detained more than 7 days (dashed red line) across the four outcomes for the full sample.[9] Panel A provides the results associated with failure to appear where we find a statistically significant difference between the groups between the pre- and post-detention periods ($\Delta$ =0.029). The DiD model includes the interaction term of treatment status and period, $\beta_3$, demonstrated a 31% increase in the odds of an FTA post-detention for individuals detained longer suggesting that pretrial detention has a criminogenic amplification effect (OR=1.31, $p<.0001$). For any new arrest, $\Delta$ =0.039 and for new violent arrest we find a small effect ($\Delta$ =0.002), which are indicative of a 40% (OR=1.40, $p< .0001$) and 25% increase in the odds of any new arrest or a new violent arrest (OR=1.25, $p<.001$). Switching from the crime related outcomes to considering the conviction status, we find that pretrial detention has a punitive effect with a .110 increase in the probability of detained individuals being convicted for their current charge (OR=1.55, $p<.001$). The findings provide clear evidence to support the criminogenic amplification effect and the punitive effect of pretrial detention for those detained

[9] The expected change for those detained at more than 7 days is equal to the change experienced by those detained 1 day or less if they started at the intercept of the defendants detained more than 7 days.

more than 7 days.[10] The full models used to produce the results in Figure 1 are provided in Table 2.

**Insert Table 3 About Here**

Table 3 provides the expected number of individuals in the full sample 16,232 to have the corresponding pretrial outcome if they were detained during pretrial for 1 day or less or detained during pretrial for more than 7 days. Table 3 shows that approximately 906 more individuals (4,181-3,275) would experience a failure to appear if the entire sample of 16,232 individuals was detained for more than 7 days. Approximately 1,016 and 339 more individuals would be arrested for any new crime or a violent crime, respectively. More than 1,580 individuals would be convicted on the current charge if the sample of 16,232 individuals was detained for more than 7 days when compared to being detained for 1 day or less. These findings highlight the implications of the effects of spending more than 7 days in pretrial detention – when compared to spending 1 day or less in pretrial detention.

## Discussion

Pretrial detention is intended to reduce missed court appearances and prevent new crimes. Prior research has demonstrated a series of negative consequences for people detained pretrial, and pretrial detention tends to be used for individuals unable to make bail as few people are denied release. Individuals detained prior to trial are innocent and have constitutional guarantees to be released, but most people held in jail are there awaiting trial. Many of the individuals detained in jail prior to trial are an especially disadvantaged group as they tend to be poor. The growth in pretrial detention led Smith (2022: 4) to ask: "has mass detention made us safer?" The

[10] To increase our confidence in our interpretations, we defined statistical significance as $p < .001$. While this decision is supported by the literature (McShane et al., 2019), we do provide the *p*-values corresponding to all the estimates in Appendices B-D.

current study starts to answer this question about whether pretrial detention achieves its goals of reducing court absences and new arrests.

The lack of rigorous studies about the effects of pretrial detention leaves us with a limited understanding of the public safety benefits of pretrial detention. The current research contributes to further expanding knowledge on the consequences of jail incarceration (Turney and Conner, 2019). Prior research about the public safety benefits of prison incarceration demonstrated little deterrent effect, and we find a similar result with jail incarceration. The research findings provide strong evidence that pretrial detention is unlikely to achieve the crime prevention goals set out for jails. Rather, being detained pretrial for more than 7 days (compared to 1 day or less) appears to increase missed court appearances, arrests, and convictions. Simply, any potential incapacitation effects are short lived with a criminogenic amplification effect and punitive effect (Dobbie et al., 2018).

There are three major implications for the criminological field. First, this study continues to demonstrate the punitive consequences of even one week in jail. We found that being detained a week or more is related to a significantly increased likelihood of conviction compared to one day or less. The consistency of the punitive effect of time spent in pretrial detention across studies suggests that pretrial detention may be best targeted toward a small subset of potentially dangerous individuals to support reforms seeking to reduce incarcerated populations. Future research should investigate whether less reliance on pretrial detention has an indirect effect on reducing incarcerated populations by reducing convictions and lowering sentence severity. Similarly, future research should explore if the punitive effects of time spent in pretrial detention are universal or differ across subgroups (e.g., race, age, risk).

Second, we found that longer time spent in pretrial detention is associated with greater likelihood for missed court appearances, new arrests, and new arrests for violent crimes. These findings are profound as we estimated that if all admitted individuals were detained for at least one week, we could expect about 1,000 more missed court appearances, 1,000 new arrests and 350 new violent crime arrests. A limitation of this study is that we are unable to discern whether the mechanism at work here is a criminogenic effect, decreased prosocial attachments upon release, or some other mechanism. More research is needed to understand the mechanisms that may be driving the worse outcomes for the detained. These results need further investigation as we are not recommending that pretrial detention be jettisoned completely. Instead, criminal justice systems need to balance individual freedoms and constitutional protections with public safety and victim concerns. That is to say that we think further research is needed to understand how tools like risk assessments or other case processing decision supports could improve outcomes. For instance, Kleinberg et al. (2018) found that if judges based their release decisions on an assessment there would be a 42% reduction in jail populations without changing rates of new arrests; alternatively, detention rates could be held constant and rates of new arrests could be reduced by 25% by releasing individuals following the assessment recommendations.

Third, this study contributes to criminological methods by using advanced approaches from the causal inference literature to apply a doubly robust DiD design (Sant'Anna and Zhao, 2020). We follow econometricians by integrating outcome regressions with inverse probability weighting to estimate the average treatment effect of the detained. In this sense, double robustness indicates that the resulting odds ratios estimate the average treatment effect for the detained even if either (but not both) the logistic regression or the inverse probability weight model are misspecified. This is one of the most robust quasi-experimental approaches to control for potential confounding from omitted variable bias and from inherent differences between the detained and release populations.

## Conclusion

The findings provide clear evidence to support the criminogenic amplification effect and the punitive effect of time spent in pretrial detention for those detained more than one week. A substantial body of research shows that postconviction incarceration is associated with a series of negative outcomes, including reduced labor market participation, damaged family bonds, and higher rates of recidivism (Western, 2006). These findings appear to carry over to the pretrial field as prior research has shown similar negative outcomes associated with even short stays in jails (Lowenkamp, 2022; Walker, 2022). Pretrial detention, therefore, not only has negative effects for detained individuals, but it also falls short of its intended public safety purposes. We see this research as providing an opportunity to take a more focused look at the use of pretrial detention to consider what are realistic expectations.

Pretrial detention has been critiqued for the past 100 years for its impact on the poor and vulnerable (Beeley, 1927). Finding that pretrial detention has a net effect of worsening court appearance and new arrests is aligned with prior research on prison incarceration. More research is needed to understand how generalizable our findings are to other jurisdictions. Coupling these findings with the punitive and collateral effects of time spent in pretrial detention, signals a need for future research to identify effective methods of release that maximize liberty, safety, and equity and minimize the criminogenic effects of pretrial detention. Jails are inhabited with pretrial detainees, detention makes outcomes worse for these detainees, and detention does not deliver on public safety as intended. We argue a more limited and targeted use of pretrial detention is needed and more research attention on alternatives to pretrial detention.

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Table 1: Descriptive Statistics.

| | Total Sample | | | Detained 1 Day or Less | | Detained More Than 7 Days | |
|---|---|---|---|---|---|---|---|
| | Mean (%) | SD | Min, Max | Mean (%) | SD | Mean (%) | SD |
| **Criminogenic Outcomes** | | | | | | | |
| Failure to Appear | 22% | -- | 0, 1 | 19% | -- | 29% | -- |
| New Criminal Arrest | 23% | -- | 0, 1 | 18% | -- | 33% | -- |
| New Violent Criminal Arrest | 7% | -- | 0, 1 | 5% | -- | 10% | -- |
| **Punitive Outcomes** | | | | | | | |
| Convicted | 46% | -- | 0, 1 | 42% | -- | 56% | -- |
| **Pre-Detention Legal System Outcomes** | | | | | | | |
| Lifetime Failure to Appear | 54% | -- | 0, 1 | 52% | -- | 60% | -- |
| Lifetime Conviction | 56% | -- | 0, 1 | 49% | -- | 71% | -- |
| Lifetime Violent Conviction | 24% | -- | 0, 1 | 17% | -- | 38% | -- |
| **Treatment** | | | | | | | |
| Detained More than 7-Days | 33% | -- | 0, 1 | | | | |
| **Covariates** | | | | | | | |
| Time at Risk (in Days)* | 161.68 | 200.72 | 1, 1083 | 152.41 | 195.06 | 190.13 | 211.32 |
| Age at Current Arrest | 34.72 | 11.67 | 18,90 | 34.53 | 11.68 | 35.10 | 11.66 |
| Current Offense Violent | 27% | -- | 0, 1 | 21% | -- | 41% | -- |
| Prior Incarcerations | 35% | -- | 0, 1 | 29% | -- | 48% | -- |
| Pending Charge | 21% | -- | 0, 1 | 19% | -- | 26% | -- |
| Total Number of Charges | 2.23 | 1.99 | 1, 79 | 1.77 | 1.20 | 3.18 | 2.80 |
| Felony^ | 50% | -- | 0, 1 | 36% | -- | 79% | -- |
| Misdemeanor | 50% | -- | 0, 1 | 64% | -- | 21% | -- |
| Drug Offense^ | 12% | -- | 0, 1 | 10% | -- | 16% | -- |
| Other Offense | 4% | -- | 0, 1 | 5% | -- | 1% | -- |
| Property Offense | 27% | -- | 0, 1 | 26% | -- | 29% | -- |
| Public Order Offense | 24% | -- | 0, 1 | 30% | -- | 11% | -- |
| Violent Offense | 34% | -- | 0, 1 | 29% | -- | 43% | -- |
| County 1^ | 49% | -- | 0, 1 | 60% | -- | 25% | -- |
| County 2 | 39% | -- | 0, 1 | 25% | -- | 66% | -- |
| County 3 | 13% | -- | 0, 1 | 15% | -- | 8% | -- |
| Non-White^ | 52% | -- | 0, 1 | 43% | -- | 69% | -- |
| White | 48% | -- | 0, 1 | 57% | -- | 31% | -- |
| Male | 72% | -- | 0, 1 | 68% | -- | 81% | -- |
| N | 16,232 | | | 10,915 | | 5,317 | |

*Notes:* "*" indicates that time at risk only served as a covariate when predicting the outcomes. "^" Identifies the Reference Category for the subsequent measures.

Table 2: Full doubly robust difference-in-difference model results predicting failure to appear, new criminal arrest, new violent criminal arrest, and conviction.

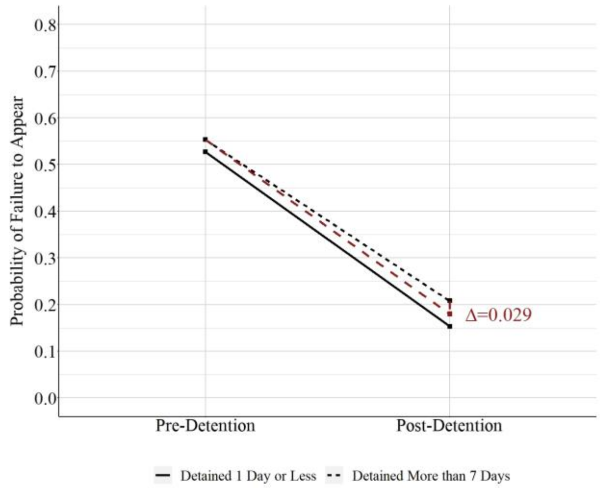
| | DV: Failure to Appear | | | DV: New Criminal Arrest | | | DV: New Violent Criminal Arrest | | | DV: Convicted | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | OR | se | p-value | OR | se | p-value | OR | se | p-value | OR | se | p-value |
| ***Key Indicators (KI*** | | | | | | | | | | | | |
| Detained more than 7 days | 1.115 | 0.025 | 0.000 | 1.090 | 0.025 | 0.001 | 1.096 | 0.029 | 0.002 | 1.059 | 0.025 | 0.022 |
| Pre-Post Pretrial Detention | 0.158 | 0.028 | 0.000 | 0.154 | 0.028 | 0.000 | 0.209 | 0.039 | 0.000 | 0.556 | 0.025 | 0.000 |
| ***Difference-in-Difference Estimator*** | | | | | | | | | | | | |
| Interaction between KI | 1.309 | 0.038 | 0.000 | 1.395 | 0.038 | 0.000 | 1.249 | 0.052 | 0.000 | 1.554 | 0.035 | 0.000 |
| ***Covariates of Interest*** | | | | | | | | | | | | |
| Age at Current Arrest | 0.995 | 0.001 | 0.000 | 1.003 | 0.001 | 0.001 | 1.006 | 0.001 | 0.000 | 1.006 | 0.001 | 0.000 |
| Current Offense Violent (County) | 0.815 | 0.037 | 0.000 | 0.991 | 0.037 | 0.804 | 1.181 | 0.047 | 0.000 | 0.927 | 0.035 | 0.030 |
| Prior Incarcerations | 3.865 | 0.021 | 0.000 | 6.336 | 0.021 | 0.000 | 6.121 | 0.027 | 0.000 | 6.598 | 0.021 | 0.000 |
| Pending Charge | 2.623 | 0.023 | 0.000 | 1.666 | 0.023 | 0.000 | 1.102 | 0.028 | 0.001 | 1.621 | 0.022 | 0.000 |
| Time at Risk | 0.999 | 0.000 | 0.000 | 0.999 | 0.000 | 0.000 | 0.999 | 0.000 | 0.000 | 0.999 | 0.000 | 0.000 |
| Total Number of Charges | 0.983 | 0.004 | 0.000 | 0.970 | 0.003 | 0.000 | 1.003 | 0.004 | 0.514 | 0.945 | 0.003 | 0.000 |
| Misdemeanor | 0.915 | 0.022 | 0.000 | 0.997 | 0.022 | 0.891 | 0.963 | 0.028 | 0.183 | 0.744 | 0.021 | 0.000 |
| Other Offense | 4.226 | 0.059 | 0.000 | 0.781 | 0.061 | 0.000 | 1.082 | 0.087 | 0.366 | 1.076 | 0.056 | 0.195 |
| Property Offense | 1.104 | 0.032 | 0.002 | 1.198 | 0.032 | 0.000 | 1.252 | 0.041 | 0.000 | 1.067 | 0.031 | 0.037 |
| Public Order Offense | 0.592 | 0.037 | 0.000 | 0.719 | 0.037 | 0.000 | 1.041 | 0.048 | 0.407 | 0.767 | 0.035 | 0.000 |
| Violent Offense (National) | 0.852 | 0.043 | 0.000 | 0.781 | 0.044 | 0.000 | 1.534 | 0.056 | 0.000 | 0.894 | 0.042 | 0.008 |
| County 2 | 0.569 | 0.027 | 0.000 | 1.560 | 0.027 | 0.000 | 1.446 | 0.034 | 0.000 | 0.984 | 0.025 | 0.511 |
| County 3 | 1.118 | 0.028 | 0.000 | 0.978 | 0.028 | 0.434 | 0.796 | 0.038 | 0.000 | 1.280 | 0.028 | 0.000 |
| White | 0.967 | 0.022 | 0.129 | 1.026 | 0.022 | 0.258 | 0.704 | 0.029 | 0.000 | 1.045 | 0.021 | 0.037 |
| Male | 1.016 | 0.021 | 0.450 | 1.317 | 0.021 | 0.000 | 1.959 | 0.031 | 0.000 | 1.199 | 0.020 | 0.000 |
| Nindividuals | | 16,232 | | | 16,232 | | | 16,232 | | | 16,232 | |

Notes: All models were weighted using an inverse probability weight calculated from the results of the binary logistic regression model in Table B1.

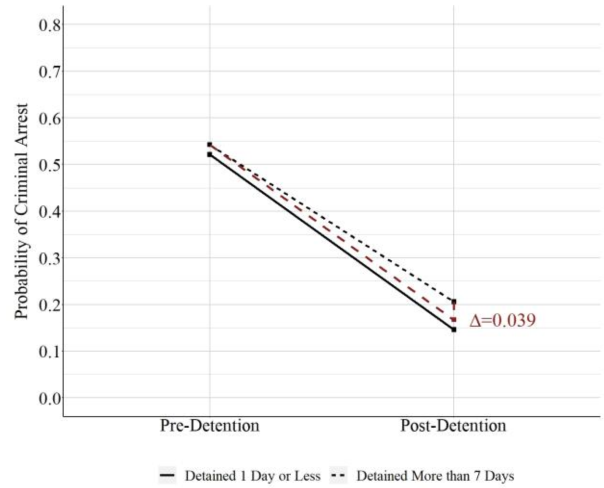
Table 3: Expected number of outcomes if the entire sample was detained for1 day or less or more than 7 days.

| | Detained for 1 Day or Less | | Detained for More than 7 days | |
|---|---|---|---|---|
| | Count | Rate | Count | Rate |
| **Criminogenic Outcomes** | | | | |
| Failure to Appear | 3275 | 0.20 | 4181 | 0.26 |
| New Criminal Arrest | 3442 | 0.21 | 4461 | 0.27 |
| New Violent Criminal Arrest | 1120 | 0.07 | 1459 | 0.10 |
| **Punitive Outcomes** | | | | |
| Convicted | 7061 | 0.44 | 8641 | 0.53 |
| N | 16,232 | | | |

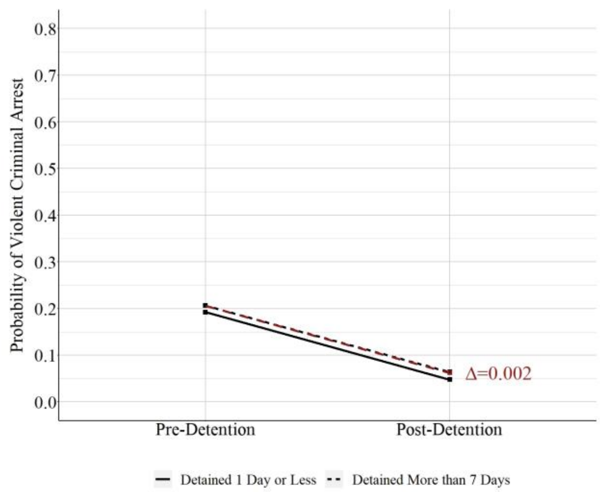
Panel A:
Failure to Appear*




Panel B:
New Criminal Arrest*




Panel C:
New Violent Criminal Arrest*




Panel D:
Convicted*

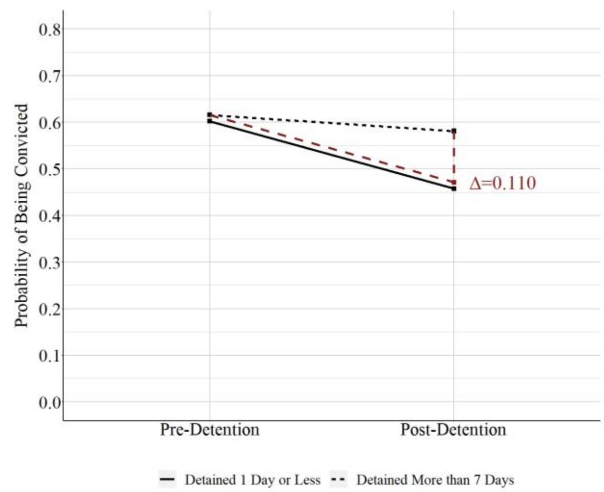



Figure 1. Plotted probabilities from doubly robust DiD model ($N_{individuals}$ = 16,232; $N_{observations}$ = 32,464).
*Notes*: The model used to estimate the inverse probability weights and the doubly robust DiD models are provided in Tables 1.
* Denotes differences were statistically significant at the $p < .001$ level.

**Appendix Materials**
**TO BE PUBLISHED ONLINE ONLY**

**Table of Contents**

## Appendix A: Balancing Statistics for the Full Sample

Table A1: Pre-weighting and Post-Weighting Differences Between Those Detained for 1 Day or Less and Those Detained for More than 7 Days.

| | Pre-Weighting | | Post-Weighing | |
|---|---|---|---|---|
| | t-value | Cohen's D | t-value | Cohen's D |
| Age at Current Arrest | -2.90 | -0.05 | -15.80 | -0.24 |
| Current Offense Violent (County) | -25.83 | -0.46 | -7.10 | -0.09 |
| Prior Incarcerations | -23.84 | -0.41 | -17.71 | -0.31 |
| Pending Charge | -10.45 | -0.18 | -10.93 | -0.21 |
| Total Number of Charges | -35.26 | -0.75 | -2.30 | -0.03 |
| Misdemeanor | 58.11 | 0.92 | -10.84 | -0.26 |
| Other Offense | 17.19 | 0.22 | -2.24 | -0.05 |
| Property Offense | -3.95 | -0.07 | -8.98 | -0.16 |
| Public Order Offense | 31.26 | 0.46 | -7.10 | -0.17 |
| Violent Offense (National) | -18.04 | -0.31 | -8.34 | -0.12 |
| County 2 | -53.39 | -0.92 | -9.33 | -0.12 |
| County 3 | 12.67 | 0.19 | -7.25 | -0.15 |
| White | 32.32 | 0.53 | -12.01 | -0.27 |
| Male | -18.06 | -0.29 | -18.84 | -0.39 |
| Prior Failure to Appear | -10.85 | -0.18 | -18.06 | -0.37 |
| Prior Criminal Arrests | -28.16 | -0.46 | -20.90 | -0.40 |
| Prior Violent Criminal Arrests | -28.61 | -0.52 | -16.21 | -0.29 |
| N | 16,232 | | | |

*Notes:* Positive values indicate that those Detained for 1 Day or Less have a higher mean value on the construct than those Detained for More than 7 Days. Negative values indicate that those Detained for 1 Day or Less have a lower mean value on the construct than those Detained for More than 7 Days. Cohen classified effect sizes as small (d = 0.2), medium (d = 0.5), and large (d ≥ 0.8)

## Appendix B: Predicting Detained More Than 7 Days

Table B1: Predicting Detained More Than 7 Days

| | DV: Detained More than 7 Days | | | | | |
|---|---|---|---|---|---|---|
| | b | se | p-value | OR | L 95% OR | U 95% OR |
| Age at Current Arrest | -0.005 | 0.002 | 0.024 | 0.995 | 0.991 | 0.999 |
| Current Offense Violent (County) | 0.570 | 0.090 | 0.000 | 1.768 | 1.482 | 2.113 |
| Prior Incarcerations | 0.772 | 0.066 | 0.000 | 2.165 | 1.904 | 2.463 |
| Pending Charge | 0.407 | 0.056 | 0.000 | 1.502 | 1.345 | 1.678 |
| Total Number of Charges | 0.319 | 0.015 | 0.000 | 1.376 | 1.336 | 1.419 |
| Misdemeanor | -1.792 | 0.055 | 0.000 | 0.167 | 0.150 | 0.185 |
| Other Offense | -1.404 | 0.182 | 0.000 | 0.246 | 0.170 | 0.347 |
| Property Offense | 0.460 | 0.071 | 0.000 | 1.584 | 1.379 | 1.822 |
| Public Order Offense | 0.849 | 0.090 | 0.000 | 2.338 | 1.961 | 2.788 |
| Violent Offense (National) | 0.853 | 0.105 | 0.000 | 2.347 | 1.909 | 2.885 |
| County 2 | 2.465 | 0.064 | 0.000 | 11.760 | 10.371 | 13.354 |
| County 3 | 0.049 | 0.072 | 0.497 | 1.050 | 0.911 | 1.208 |
| White | -0.021 | 0.053 | 0.693 | 0.979 | 0.883 | 1.086 |
| Male | 0.345 | 0.052 | 0.000 | 1.413 | 1.276 | 1.565 |
| Prior Failure to Appear | 0.492 | 0.062 | 0.000 | 1.636 | 1.449 | 1.847 |
| Prior Criminal Arrests | 0.328 | 0.065 | 0.000 | 1.388 | 1.223 | 1.576 |
| Prior Violent Criminal Arrests | 0.327 | 0.059 | 0.000 | 1.387 | 1.235 | 1.559 |
| $N_{individuals}$ | 16,232 | | | | | |

Table B2: Predicting Detained more Than 7 Days (Male Subsample).

| | DV: Detained More than 7 Days | | | | | |
|---|---|---|---|---|---|---|
| | b | se | p-value | OR | L 95% OR | U 95% OR |
| Age at Current Arrest | -0.002 | 0.002 | 0.298 | 0.998 | 0.993 | 1.002 |
| Current Offense Violent (County) | 0.579 | 0.102 | 0.000 | 1.785 | 1.463 | 2.184 |
| Prior Incarcerations | 0.688 | 0.076 | 0.000 | 1.990 | 1.715 | 2.310 |
| Pending Charge | 0.304 | 0.065 | 0.000 | 1.355 | 1.193 | 1.539 |
| Total Number of Charges | 0.324 | 0.018 | 0.000 | 1.383 | 1.336 | 1.432 |
| Misdemeanor | -1.744 | 0.063 | 0.000 | 0.175 | 0.154 | 0.198 |
| Other Offense | -1.308 | 0.201 | 0.000 | 0.270 | 0.180 | 0.397 |
| Property Offense | 0.591 | 0.082 | 0.000 | 1.805 | 1.538 | 2.119 |
| Public Order Offense | 0.919 | 0.102 | 0.000 | 2.506 | 2.053 | 3.063 |
| Violent Offense (National) | 0.880 | 0.119 | 0.000 | 2.411 | 1.908 | 3.046 |
| County 2 | 2.532 | 0.073 | 0.000 | 12.576 | 10.903 | 14.535 |
| County 3 | 0.126 | 0.083 | 0.126 | 1.135 | 0.964 | 1.333 |
| White | -0.086 | 0.060 | 0.153 | 0.917 | 0.815 | 1.033 |
| Prior Failure to Appear | 0.488 | 0.071 | 0.000 | 1.628 | 1.418 | 1.871 |
| Prior Criminal Arrests | 0.233 | 0.076 | 0.002 | 1.262 | 1.088 | 1.464 |
| Prior Violent Criminal Arrests | 0.343 | 0.067 | 0.000 | 1.409 | 1.236 | 1.607 |
| $N_{individuals}$ | | | | 11,734 | | |

Table B3: Predicting Detained more Than 7 Days (Female Subsample)

| | DV: Detained More than 7 Days | | | | | |
|---|---|---|---|---|---|---|
| | b | se | p-value | OR | L 95% OR | U 95% OR |
| Age at Current Arrest | -0.011 | 0.004 | 0.013 | 0.989 | 0.980 | 0.998 |
| Current Offense Violent (County) | 0.490 | 0.198 | 0.014 | 1.632 | 1.112 | 2.422 |
| Prior Incarcerations | 1.074 | 0.133 | 0.000 | 2.928 | 2.259 | 3.808 |
| Pending Charge | 0.671 | 0.113 | 0.000 | 1.957 | 1.568 | 2.443 |
| Total Number of Charges | 0.315 | 0.031 | 0.000 | 1.371 | 1.292 | 1.457 |
| Misdemeanor | -1.955 | 0.114 | 0.000 | 0.142 | 0.113 | 0.177 |
| Other Offense | -1.725 | 0.435 | 0.000 | 0.178 | 0.070 | 0.394 |
| Property Offense | 0.112 | 0.146 | 0.441 | 1.119 | 0.842 | 1.492 |
| Public Order Offense | 0.747 | 0.192 | 0.000 | 2.110 | 1.449 | 3.075 |
| Violent Offense (National) | 0.927 | 0.229 | 0.000 | 2.527 | 1.611 | 3.949 |
| County 2 | 2.307 | 0.138 | 0.000 | 10.043 | 7.691 | 13.199 |
| County 3 | -0.189 | 0.147 | 0.198 | 0.828 | 0.619 | 1.100 |
| White | 0.159 | 0.109 | 0.145 | 1.173 | 0.947 | 1.455 |
| Prior Failure to Appear | 0.513 | 0.130 | 0.000 | 1.670 | 1.294 | 2.158 |
| Prior Criminal Arrests | 0.507 | 0.128 | 0.000 | 1.659 | 1.292 | 2.131 |
| Prior Violent Criminal Arrests | 0.427 | 0.133 | 0.001 | 1.532 | 1.180 | 1.988 |
| $N_{individuals}$ | 4,498 | | | | | |

Table B4: Predicting Detained more Than 7 Days (White Subsample)

| | DV: Detained More than 7 Days | | | | | |
|---|---|---|---|---|---|---|
| | b | se | p-value | OR | L 95% OR | U 95% OR |
| Age at Current Arrest | -0.008 | 0.003 | 0.009 | 0.992 | 0.986 | 0.998 |
| Current Offense Violent (County) | 0.385 | 0.134 | 0.004 | 1.469 | 1.133 | 1.913 |
| Prior Incarcerations | 0.782 | 0.095 | 0.000 | 2.186 | 1.817 | 2.635 |
| Pending Charge | 0.361 | 0.078 | 0.000 | 1.434 | 1.232 | 1.670 |
| Total Number of Charges | 0.326 | 0.022 | 0.000 | 1.386 | 1.327 | 1.449 |
| Misdemeanor | -1.508 | 0.084 | 0.000 | 0.221 | 0.188 | 0.261 |
| Other Offense | -2.168 | 0.487 | 0.000 | 0.114 | 0.039 | 0.271 |
| Property Offense | 0.196 | 0.103 | 0.057 | 1.217 | 0.995 | 1.491 |
| Public Order Offense | 0.605 | 0.129 | 0.000 | 1.830 | 1.423 | 2.358 |
| Violent Offense (National) | 0.552 | 0.150 | 0.000 | 1.736 | 1.292 | 2.328 |
| County 2 | 2.473 | 0.108 | 0.000 | 11.853 | 9.609 | 14.662 |
| County 3 | 0.032 | 0.083 | 0.702 | 1.032 | 0.876 | 1.214 |
| White | 0.121 | 0.076 | 0.110 | 1.128 | 0.973 | 1.309 |
| Prior Failure to Appear | 0.643 | 0.102 | 0.000 | 1.903 | 1.559 | 2.326 |
| Prior Criminal Arrests | 0.278 | 0.100 | 0.006 | 1.321 | 1.084 | 1.607 |
| Prior Violent Criminal Arrests | 0.265 | 0.084 | 0.002 | 1.304 | 1.106 | 1.537 |
| $N_{individuals}$ | 7,829 | | | | | |

Table B5: Predicting Detained more Than 7 Days (Black Subsample)

| | DV: Detained More than 7 Days | | | | | |
|---|---|---|---|---|---|---|
| | b | se | p-value | OR | L 95% OR | U 95% OR |
| Age at Current Arrest | 0.001 | 0.003 | 0.813 | 1.001 | 0.995 | 1.007 |
| Current Offense Violent (County) | 0.777 | 0.141 | 0.000 | 2.175 | 1.655 | 2.873 |
| Prior Incarcerations | 0.790 | 0.101 | 0.000 | 2.204 | 1.808 | 2.688 |
| Pending Charge | 0.425 | 0.091 | 0.000 | 1.529 | 1.281 | 1.828 |
| Total Number of Charges | 0.316 | 0.023 | 0.000 | 1.372 | 1.312 | 1.436 |
| Misdemeanor | -2.117 | 0.080 | 0.000 | 0.120 | 0.103 | 0.141 |
| Other Offense | -0.864 | 0.210 | 0.000 | 0.422 | 0.276 | 0.630 |
| Property Offense | 0.782 | 0.104 | 0.000 | 2.186 | 1.785 | 2.679 |
| Public Order Offense | 0.965 | 0.136 | 0.000 | 2.624 | 2.010 | 3.427 |
| Violent Offense (National) | 1.186 | 0.164 | 0.000 | 3.275 | 2.374 | 4.519 |
| County 2 | 2.515 | 0.097 | 0.000 | 12.370 | 10.238 | 15.003 |
| County 3 | 0.139 | 0.221 | 0.528 | 1.149 | 0.740 | 1.761 |
| White | 0.679 | 0.079 | 0.000 | 1.971 | 1.688 | 2.304 |
| Prior Failure to Appear | 0.396 | 0.084 | 0.000 | 1.485 | 1.259 | 1.752 |
| Prior Criminal Arrests | 0.312 | 0.092 | 0.001 | 1.366 | 1.141 | 1.636 |
| Prior Violent Criminal Arrests | 0.417 | 0.094 | 0.000 | 1.517 | 1.263 | 1.822 |
| $N_{individuals}$ | 7,160 | | | | | |

# Appendix C: Race and Sex Full Model Results

Table C1: Full doubly robust difference-in-different model results predicting failure to appear, convicted and sentenced, new criminal arrest, and new violent criminal arrest (Male Subsample)

| | DV: Failure to Appear | | | | | | DV: Convicted | | | | | | DV: New Criminal Arrest | | | | | | DV: New Violent Criminal Arrest | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | b | se | p-value | OR | L 95% OR | U 95% OR | b | se | p-value | OR | L 95% OR | U 95% OR | b | se | p-value | OR | L 95% OR | U 95% OR | b | se | p-value | OR | L 95% OR | U 95% OR |
| ***Key Indicators (KI)*** | | | | | | | | | | | | | | | | | | | | | | | | |
| Detained more than 7 days | 0.106 | 0.029 | 0.000 | 1.112 | 1.050 | 1.177 | 0.077 | 0.030 | 0.010 | 1.080 | 1.019 | 1.145 | 0.097 | 0.030 | 0.001 | 1.102 | 1.040 | 1.167 | 0.068 | 0.032 | 0.034 | 1.071 | 1.005 | 1.140 |
| Pre-Post Pretrial Detention | -1.818 | 0.033 | 0.000 | 0.162 | 0.152 | 0.173 | -0.694 | 0.030 | 0.000 | 0.499 | 0.471 | 0.530 | -1.869 | 0.033 | 0.000 | 0.154 | 0.145 | 0.165 | -1.583 | 0.042 | 0.000 | 0.205 | 0.189 | 0.223 |
| ***Difference-in-Difference Estimator*** | | | | | | | | | | | | | | | | | | | | | | | | |
| Interaction between KI | 0.168 | 0.044 | 0.000 | 1.183 | 1.084 | 1.290 | 0.315 | 0.042 | 0.000 | 1.370 | 1.262 | 1.488 | 0.120 | 0.044 | 0.006 | 1.128 | 1.034 | 1.229 | 0.123 | 0.057 | 0.031 | 1.131 | 1.011 | 1.266 |
| ***Covariates of Interest*** | | | | | | | | | | | | | | | | | | | | | | | | |
| Age at Current Arrest | -0.002 | 0.001 | 0.018 | 0.998 | 0.996 | 1.000 | 0.007 | 0.001 | 0.000 | 1.007 | 1.005 | 1.009 | 0.005 | 0.001 | 0.000 | 1.005 | 1.003 | 1.007 | 0.009 | 0.001 | 0.000 | 1.009 | 1.006 | 1.011 |
| Current Offense Violent (County) | -0.218 | 0.043 | 0.000 | 0.804 | 0.739 | 0.875 | 0.017 | 0.041 | 0.673 | 1.017 | 0.939 | 1.102 | -0.039 | 0.043 | 0.369 | 0.962 | 0.884 | 1.047 | 0.118 | 0.051 | 0.021 | 1.125 | 1.018 | 1.244 |
| Prior Incarcerations | 1.352 | 0.024 | 0.000 | 3.864 | 3.686 | 4.051 | 1.863 | 0.024 | 0.000 | 6.442 | 6.148 | 6.751 | 1.774 | 0.025 | 0.000 | 5.894 | 5.614 | 6.190 | 1.755 | 0.030 | 0.000 | 5.782 | 5.452 | 6.135 |
| Pending Charge | 0.911 | 0.026 | 0.000 | 2.486 | 2.361 | 2.619 | 0.420 | 0.026 | 0.000 | 1.522 | 1.445 | 1.602 | 0.416 | 0.027 | 0.000 | 1.516 | 1.439 | 1.597 | 0.045 | 0.031 | 0.150 | 1.046 | 0.984 | 1.113 |
| Time at Risk | -0.001 | 0.000 | 0.000 | 0.999 | 0.999 | 0.999 | -0.001 | 0.000 | 0.000 | 0.999 | 0.999 | 0.999 | -0.001 | 0.000 | 0.000 | 0.999 | 0.999 | 0.999 | -0.001 | 0.000 | 0.000 | 0.999 | 0.999 | 0.999 |
| Total Number of Charges | 0.044 | 0.005 | 0.000 | 1.045 | 1.034 | 1.055 | -0.013 | 0.005 | 0.009 | 0.987 | 0.978 | 0.997 | 0.031 | 0.005 | 0.000 | 1.032 | 1.021 | 1.042 | 0.078 | 0.006 | 0.000 | 1.081 | 1.069 | 1.093 |
| Misdemeanor | -0.044 | 0.026 | 0.090 | 0.957 | 0.909 | 1.007 | -0.271 | 0.025 | 0.000 | 0.762 | 0.727 | 0.800 | 0.035 | 0.026 | 0.172 | 1.036 | 0.985 | 1.090 | 0.029 | 0.032 | 0.353 | 1.030 | 0.968 | 1.096 |
| Other Offense | 1.405 | 0.071 | 0.000 | 4.075 | 3.545 | 4.685 | 0.087 | 0.068 | 0.198 | 1.091 | 0.955 | 1.245 | -0.168 | 0.073 | 0.021 | 0.845 | 0.733 | 0.975 | 0.098 | 0.097 | 0.309 | 1.103 | 0.911 | 1.331 |
| Property Offense | 0.111 | 0.037 | 0.003 | 1.118 | 1.040 | 1.202 | 0.063 | 0.036 | 0.085 | 1.065 | 0.991 | 1.144 | 0.214 | 0.037 | 0.000 | 1.239 | 1.152 | 1.332 | 0.215 | 0.045 | 0.000 | 1.240 | 1.136 | 1.355 |
| Public Order Offense | -0.466 | 0.042 | 0.000 | 0.627 | 0.578 | 0.681 | -0.232 | 0.041 | 0.000 | 0.793 | 0.733 | 0.859 | -0.231 | 0.042 | 0.000 | 0.793 | 0.731 | 0.862 | 0.029 | 0.053 | 0.588 | 1.029 | 0.928 | 1.142 |
| Violent Offense (National) | -0.071 | 0.050 | 0.157 | 0.931 | 0.844 | 1.028 | -0.154 | 0.049 | 0.002 | 0.857 | 0.779 | 0.943 | -0.107 | 0.051 | 0.035 | 0.899 | 0.814 | 0.993 | 0.451 | 0.061 | 0.000 | 1.570 | 1.393 | 1.770 |
| County 2 | -0.518 | 0.032 | 0.000 | 0.595 | 0.560 | 0.633 | 0.027 | 0.030 | 0.371 | 1.027 | 0.969 | 1.088 | 0.503 | 0.031 | 0.000 | 1.654 | 1.555 | 1.759 | 0.309 | 0.038 | 0.000 | 1.362 | 1.265 | 1.468 |
| County 3 | 0.148 | 0.033 | 0.000 | 1.160 | 1.086 | 1.238 | 0.230 | 0.034 | 0.000 | 1.259 | 1.179 | 1.345 | -0.013 | 0.034 | 0.706 | 0.987 | 0.924 | 1.055 | -0.207 | 0.042 | 0.000 | 0.813 | 0.748 | 0.884 |
| White | -0.098 | 0.026 | 0.000 | 0.907 | 0.861 | 0.955 | 0.028 | 0.025 | 0.264 | 1.028 | 0.979 | 1.080 | -0.066 | 0.026 | 0.012 | 0.936 | 0.889 | 0.986 | -0.396 | 0.033 | 0.000 | 0.673 | 0.632 | 0.718 |
| $N_{individuals}$ | | | | 11,734 | | | | | | 11,734 | | | | | | 11,734 | | | | | | 11,734 | | |

*Notes*: All models were weighted using an inverse probability weight calculated from the results of the binary logistic regression model in Table B2.

Table C2: Full doubly robust difference-in-different model results predicting failure to appear, convicted and sentenced, new criminal arrest, and new violent criminal arrest (Female Subsample)

| | DV: Failure to Appear | | | | | | DV: Convicted | | | | | | DV: New Criminal Arrest | | | | | | DV: New Violent Criminal Arrest | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | b | se | p-value | OR | L 95% OR | U 95% OR | b | se | p-value | OR | L 95% OR | U 95% OR | b | se | p-value | OR | L 95% OR | U 95% OR | b | se | p-value | OR | L 95% OR | U 95% OR |
| ***Key Indicators (KI)*** | | | | | | | | | | | | | | | | | | | | | | | | |
| Detained more than 7 days | 0.097 | 0.046 | 0.036 | 1.102 | 1.006 | 1.207 | -0.057 | 0.047 | 0.228 | 0.945 | 0.862 | 1.036 | -0.011 | 0.047 | 0.811 | 0.989 | 0.902 | 1.084 | 0.106 | 0.068 | 0.115 | 1.112 | 0.974 | 1.270 |
| Pre-Post Pretrial Detention | -1.914 | 0.053 | 0.000 | 0.148 | 0.133 | 0.164 | -0.384 | 0.047 | 0.000 | 0.681 | 0.621 | 0.746 | -1.928 | 0.057 | 0.000 | 0.145 | 0.130 | 0.163 | -1.298 | 0.092 | 0.000 | 0.273 | 0.227 | 0.326 |
| ***Difference-in-Difference Estimator*** | | | | | | | | | | | | | | | | | | | | | | | | |
| Interaction between KI | 0.544 | 0.071 | 0.000 | 1.723 | 1.498 | 1.981 | 0.795 | 0.066 | 0.000 | 2.215 | 1.946 | 2.521 | 0.925 | 0.074 | 0.000 | 2.521 | 2.179 | 2.918 | 0.351 | 0.121 | 0.004 | 1.421 | 1.121 | 1.805 |
| ***Covariates of Interest*** | | | | | | | | | | | | | | | | | | | | | | | | |
| Age at Current Arrest | -0.010 | 0.002 | 0.000 | 0.990 | 0.987 | 0.993 | 0.008 | 0.002 | 0.000 | 1.008 | 1.005 | 1.011 | 0.003 | 0.002 | 0.059 | 1.003 | 1.000 | 1.007 | 0.009 | 0.003 | 0.000 | 1.010 | 1.004 | 1.015 |
| Current Offense Violent (County) | -0.115 | 0.072 | 0.110 | 0.891 | 0.774 | 1.027 | -0.202 | 0.067 | 0.003 | 0.817 | 0.716 | 0.932 | 0.165 | 0.077 | 0.032 | 1.179 | 1.015 | 1.371 | 0.507 | 0.117 | 0.000 | 1.661 | 1.324 | 2.093 |
| Prior Incarcerations | 1.196 | 0.043 | 0.000 | 3.307 | 3.042 | 3.596 | 1.887 | 0.044 | 0.000 | 6.603 | 6.062 | 7.197 | 1.961 | 0.044 | 0.000 | 7.110 | 6.526 | 7.750 | 1.846 | 0.062 | 0.000 | 6.332 | 5.608 | 7.157 |
| Pending Charge | 0.985 | 0.044 | 0.000 | 2.678 | 2.460 | 2.918 | 0.569 | 0.042 | 0.000 | 1.766 | 1.626 | 1.919 | 0.589 | 0.044 | 0.000 | 1.802 | 1.652 | 1.964 | 0.086 | 0.068 | 0.201 | 1.090 | 0.954 | 1.244 |
| Time at Risk | -0.001 | 0.000 | 0.000 | 0.999 | 0.999 | 0.999 | -0.001 | 0.000 | 0.000 | 0.999 | 0.999 | 0.999 | 0.000 | 0.000 | 0.000 | 1.000 | 0.999 | 1.000 | -0.002 | 0.000 | 0.000 | 0.998 | 0.998 | 0.999 |
| Total Number of Charges | -0.046 | 0.006 | 0.000 | 0.955 | 0.944 | 0.967 | -0.070 | 0.005 | 0.000 | 0.933 | 0.923 | 0.943 | -0.061 | 0.006 | 0.000 | 0.941 | 0.930 | 0.952 | -0.127 | 0.014 | 0.000 | 0.881 | 0.855 | 0.905 |
| Misdemeanor | -0.061 | 0.042 | 0.149 | 0.941 | 0.866 | 1.022 | -0.329 | 0.040 | 0.000 | 0.719 | 0.666 | 0.778 | -0.015 | 0.043 | 0.724 | 0.985 | 0.905 | 1.072 | -0.256 | 0.064 | 0.000 | 0.774 | 0.683 | 0.877 |
| Other Offense | 1.469 | 0.110 | 0.000 | 4.344 | 3.505 | 5.388 | 0.142 | 0.108 | 0.187 | 1.153 | 0.933 | 1.422 | -0.552 | 0.123 | 0.000 | 0.576 | 0.452 | 0.731 | -0.449 | 0.263 | 0.087 | 0.638 | 0.371 | 1.044 |
| Property Offense | 0.079 | 0.064 | 0.219 | 1.082 | 0.954 | 1.227 | 0.091 | 0.062 | 0.142 | 1.096 | 0.970 | 1.237 | 0.115 | 0.065 | 0.075 | 1.122 | 0.989 | 1.274 | 0.463 | 0.107 | 0.000 | 1.589 | 1.292 | 1.966 |
| Public Order Offense | -0.486 | 0.076 | 0.000 | 0.615 | 0.530 | 0.714 | -0.124 | 0.073 | 0.090 | 0.884 | 0.766 | 1.020 | -0.416 | 0.078 | 0.000 | 0.660 | 0.566 | 0.768 | 0.418 | 0.124 | 0.001 | 1.518 | 1.192 | 1.940 |
| Violent Offense (National) | -0.357 | 0.087 | 0.000 | 0.700 | 0.590 | 0.830 | 0.012 | 0.083 | 0.889 | 1.012 | 0.859 | 1.191 | -0.512 | 0.091 | 0.000 | 0.600 | 0.501 | 0.717 | 0.442 | 0.146 | 0.002 | 1.556 | 1.168 | 2.070 |
| County 2 | -0.747 | 0.052 | 0.000 | 0.474 | 0.428 | 0.525 | -0.246 | 0.048 | 0.000 | 0.782 | 0.711 | 0.859 | 0.226 | 0.053 | 0.000 | 1.253 | 1.130 | 1.389 | 0.504 | 0.081 | 0.000 | 1.655 | 1.413 | 1.938 |
| County 3 | 0.044 | 0.051 | 0.380 | 1.045 | 0.947 | 1.154 | 0.289 | 0.050 | 0.000 | 1.334 | 1.211 | 1.471 | -0.089 | 0.053 | 0.094 | 0.915 | 0.825 | 1.015 | -0.150 | 0.083 | 0.071 | 0.861 | 0.731 | 1.011 |
| White | 0.157 | 0.042 | 0.000 | 1.170 | 1.078 | 1.270 | 0.006 | 0.040 | 0.871 | 1.006 | 0.931 | 1.088 | 0.218 | 0.043 | 0.000 | 1.244 | 1.143 | 1.354 | -0.349 | 0.066 | 0.000 | 0.705 | 0.620 | 0.802 |
| $N_{individuals}$ | | | | 4,498 | | | | | | 4,498 | | | | | | 4,498 | | | | | | 4,498 | | |

*Notes*: All models were weighted using an inverse probability weight calculated from the results of the binary logistic regression model in Table B3.

Table C3: Full doubly robust difference-in-different model results predicting failure to appear, convicted and sentenced, new criminal arrest, and new violent criminal arrest (White Subsample)

| | DV: Failure to Appear | | | | | | DV: Convicted | | | | | | DV: New Criminal Arrest | | | | | | DV: New Violent Criminal Arrest | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | b | se | p-value | OR | L 95% OR | U 95% OR | b | se | p-value | OR | L 95% OR | U 95% OR | b | se | p-value | OR | L 95% OR | U 95% OR | b | se | p-value | OR | L 95% OR | U 95% OR |
| ***Key Indicators (KI)*** | | | | | | | | | | | | | | | | | | | | | | | | |
| Detained more than 7 days | 0.015 | 0.037 | 0.686 | 1.015 | 0.944 | 1.091 | -0.031 | 0.036 | 0.389 | 0.969 | 0.903 | 1.041 | -0.010 | 0.037 | 0.781 | 0.990 | 0.922 | 1.063 | -0.011 | 0.044 | 0.811 | 0.989 | 0.907 | 1.079 |
| Pre-Post Pretrial Detention | -2.091 | 0.041 | 0.000 | 0.124 | 0.114 | 0.134 | -0.534 | 0.036 | 0.000 | 0.586 | 0.547 | 0.629 | -2.214 | 0.043 | 0.000 | 0.109 | 0.101 | 0.119 | -1.637 | 0.062 | 0.000 | 0.195 | 0.172 | 0.219 |
| ***Difference-in-Difference Estimator*** | | | | | | | | | | | | | | | | | | | | | | | | |
| Interaction between KI | 0.363 | 0.055 | 0.000 | 1.438 | 1.290 | 1.603 | 0.507 | 0.051 | 0.000 | 1.660 | 1.502 | 1.835 | 0.426 | 0.057 | 0.000 | 1.531 | 1.371 | 1.711 | 0.469 | 0.082 | 0.000 | 1.598 | 1.361 | 1.878 |
| ***Covariates of Interest*** | | | | | | | | | | | | | | | | | | | | | | | | |
| Age at Current Arrest | -0.008 | 0.001 | 0.000 | 0.992 | 0.990 | 0.995 | 0.001 | 0.001 | 0.227 | 1.001 | 0.999 | 1.004 | 0.004 | 0.001 | 0.002 | 1.004 | 1.001 | 1.006 | 0.011 | 0.002 | 0.000 | 1.011 | 1.008 | 1.015 |
| Current Offense Violent (County) | -0.217 | 0.054 | 0.000 | 0.805 | 0.724 | 0.895 | -0.114 | 0.050 | 0.023 | 0.892 | 0.809 | 0.984 | -0.205 | 0.055 | 0.000 | 0.815 | 0.731 | 0.908 | 0.302 | 0.069 | 0.000 | 1.352 | 1.182 | 1.548 |
| Prior Incarcerations | 1.359 | 0.031 | 0.000 | 3.892 | 3.665 | 4.135 | 1.773 | 0.030 | 0.000 | 5.890 | 5.558 | 6.244 | 1.932 | 0.032 | 0.000 | 6.901 | 6.478 | 7.355 | 1.815 | 0.043 | 0.000 | 6.144 | 5.650 | 6.686 |
| Pending Charge | 0.921 | 0.033 | 0.000 | 2.513 | 2.355 | 2.682 | 0.306 | 0.032 | 0.000 | 1.358 | 1.276 | 1.445 | 0.432 | 0.033 | 0.000 | 1.540 | 1.443 | 1.644 | 0.114 | 0.043 | 0.009 | 1.120 | 1.029 | 1.219 |
| Time at Risk | -0.002 | 0.000 | 0.000 | 0.998 | 0.998 | 0.998 | -0.001 | 0.000 | 0.000 | 0.999 | 0.999 | 0.999 | -0.001 | 0.000 | 0.000 | 0.999 | 0.999 | 0.999 | -0.001 | 0.000 | 0.000 | 0.999 | 0.999 | 0.999 |
| Total Number of Charges | 0.043 | 0.007 | 0.000 | 1.044 | 1.029 | 1.058 | 0.026 | 0.007 | 0.000 | 1.027 | 1.013 | 1.040 | 0.043 | 0.007 | 0.000 | 1.044 | 1.029 | 1.059 | 0.010 | 0.010 | 0.305 | 1.010 | 0.991 | 1.030 |
| Misdemeanor | -0.075 | 0.032 | 0.019 | 0.928 | 0.872 | 0.988 | -0.274 | 0.029 | 0.000 | 0.760 | 0.718 | 0.805 | 0.036 | 0.032 | 0.260 | 1.037 | 0.974 | 1.105 | -0.041 | 0.043 | 0.332 | 0.960 | 0.883 | 1.043 |
| Other Offense | 1.497 | 0.141 | 0.000 | 4.470 | 3.392 | 5.897 | 0.801 | 0.128 | 0.000 | 2.229 | 1.734 | 2.868 | -0.718 | 0.151 | 0.000 | 0.488 | 0.361 | 0.654 | -1.007 | 0.349 | 0.004 | 0.365 | 0.172 | 0.688 |
| Property Offense | 0.044 | 0.049 | 0.364 | 1.045 | 0.950 | 1.149 | 0.219 | 0.046 | 0.000 | 1.245 | 1.137 | 1.363 | 0.081 | 0.049 | 0.098 | 1.084 | 0.985 | 1.193 | 0.232 | 0.069 | 0.001 | 1.261 | 1.102 | 1.445 |
| Public Order Offense | -0.704 | 0.053 | 0.000 | 0.495 | 0.445 | 0.549 | -0.120 | 0.050 | 0.016 | 0.887 | 0.804 | 0.978 | -0.395 | 0.054 | 0.000 | 0.674 | 0.606 | 0.749 | 0.061 | 0.077 | 0.423 | 1.063 | 0.916 | 1.236 |
| Violent Offense (National) | -0.427 | 0.063 | 0.000 | 0.653 | 0.576 | 0.739 | -0.057 | 0.060 | 0.344 | 0.945 | 0.841 | 1.062 | -0.256 | 0.064 | 0.000 | 0.774 | 0.682 | 0.878 | 0.589 | 0.086 | 0.000 | 1.803 | 1.524 | 2.134 |
| County 2 | -0.702 | 0.054 | 0.000 | 0.496 | 0.446 | 0.550 | 0.008 | 0.044 | 0.857 | 1.008 | 0.924 | 1.099 | 0.456 | 0.049 | 0.000 | 1.578 | 1.433 | 1.738 | 0.227 | 0.073 | 0.002 | 1.255 | 1.085 | 1.447 |
| County 3 | 0.092 | 0.035 | 0.008 | 1.096 | 1.024 | 1.173 | 0.233 | 0.033 | 0.000 | 1.263 | 1.183 | 1.348 | -0.111 | 0.035 | 0.002 | 0.895 | 0.835 | 0.959 | -0.307 | 0.047 | 0.000 | 0.735 | 0.670 | 0.806 |
| Male | -0.126 | 0.031 | 0.000 | 0.882 | 0.830 | 0.936 | 0.082 | 0.028 | 0.004 | 1.086 | 1.027 | 1.148 | 0.057 | 0.031 | 0.070 | 1.058 | 0.995 | 1.126 | 0.561 | 0.047 | 0.000 | 1.752 | 1.599 | 1.923 |
| $N_{individuals}$ | 7,829 | | | | | | 7,829 | | | | | | 7,829 | | | | | | 7,829 | | | | | |

*Notes*: All models were weighted using an inverse probability weight calculated from the results of the binary logistic regression model in Table B4.

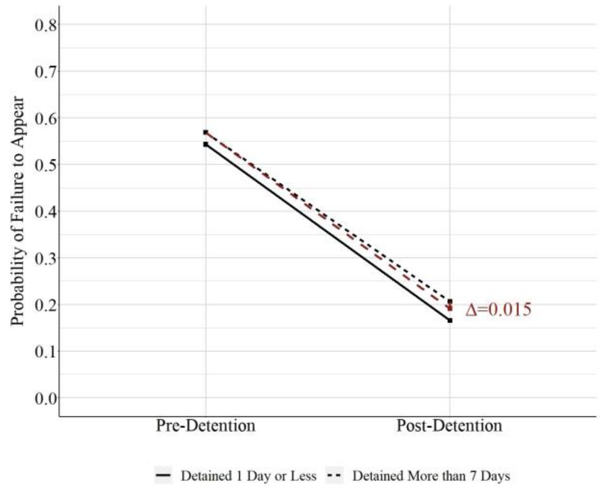
Table C4: Full doubly robust difference-in-different model results predicting failure to appear, convicted and sentenced, new criminal arrest, and new violent criminal arrest (Black Subsample)

| | DV: Failure to Appear | | | | | | DV: Convicted | | | | | | DV: New Criminal Arrest | | | | | | DV: New Violent Criminal Arrest | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | b | se | p-value | OR | L 95% OR | U 95% OR | b | se | p-value | OR | L 95% OR | U 95% OR | b | se | p-value | OR | L 95% OR | U 95% OR | b | se | p-value | OR | L 95% OR | U 95% OR |
| ***Key Indicators (KI)*** | | | | | | | | | | | | | | | | | | | | | | | | |
| Detained more than 7 days | 0.044 | 0.037 | 0.229 | 1.045 | 0.973 | 1.123 | 0.111 | 0.038 | 0.004 | 1.117 | 1.037 | 1.204 | 0.141 | 0.037 | 0.000 | 1.151 | 1.070 | 1.239 | 0.212 | 0.041 | 0.000 | 1.236 | 1.140 | 1.340 |
| Pre-Post Pretrial Detention | -1.661 | 0.042 | 0.000 | 0.190 | 0.175 | 0.206 | -0.828 | 0.039 | 0.000 | 0.437 | 0.405 | 0.472 | -1.617 | 0.041 | 0.000 | 0.198 | 0.183 | 0.215 | -1.587 | 0.053 | 0.000 | 0.205 | 0.184 | 0.227 |
| ***Difference-in-Difference Estimator*** | | | | | | | | | | | | | | | | | | | | | | | | |
| Interaction between KI | 0.351 | 0.056 | 0.000 | 1.420 | 1.271 | 1.586 | 0.356 | 0.054 | 0.000 | 1.428 | 1.284 | 1.587 | 0.172 | 0.056 | 0.002 | 1.187 | 1.065 | 1.324 | 0.019 | 0.072 | 0.795 | 1.019 | 0.885 | 1.174 |
| ***Covariates of Interest*** | | | | | | | | | | | | | | | | | | | | | | | | |
| Age at Current Arrest | -0.002 | 0.001 | 0.154 | 0.998 | 0.996 | 1.001 | 0.014 | 0.001 | 0.000 | 1.014 | 1.012 | 1.017 | 0.004 | 0.001 | 0.002 | 1.004 | 1.001 | 1.006 | 0.002 | 0.002 | 0.238 | 1.002 | 0.999 | 1.005 |
| Current Offense Violent (County) | -0.324 | 0.056 | 0.000 | 0.723 | 0.648 | 0.807 | 0.068 | 0.055 | 0.215 | 1.071 | 0.961 | 1.193 | 0.038 | 0.057 | 0.506 | 1.039 | 0.929 | 1.161 | 0.085 | 0.069 | 0.223 | 1.088 | 0.950 | 1.247 |
| Prior Incarcerations | 1.275 | 0.033 | 0.000 | 3.578 | 3.357 | 3.814 | 1.845 | 0.033 | 0.000 | 6.326 | 5.933 | 6.749 | 1.694 | 0.033 | 0.000 | 5.441 | 5.098 | 5.808 | 1.921 | 0.040 | 0.000 | 6.829 | 6.318 | 7.385 |
| Pending Charge | 0.893 | 0.035 | 0.000 | 2.442 | 2.281 | 2.614 | 0.537 | 0.036 | 0.000 | 1.711 | 1.595 | 1.836 | 0.470 | 0.036 | 0.000 | 1.601 | 1.493 | 1.716 | 0.025 | 0.042 | 0.550 | 1.025 | 0.945 | 1.113 |
| Time at Risk | -0.001 | 0.000 | 0.000 | 0.999 | 0.999 | 0.999 | -0.001 | 0.000 | 0.000 | 0.999 | 0.999 | 0.999 | -0.001 | 0.000 | 0.000 | 0.999 | 0.998 | 0.999 | -0.001 | 0.000 | 0.000 | 0.999 | 0.999 | 0.999 |
| Total Number of Charges | -0.034 | 0.005 | 0.000 | 0.966 | 0.958 | 0.975 | -0.086 | 0.005 | 0.000 | 0.917 | 0.909 | 0.925 | -0.055 | 0.004 | 0.000 | 0.947 | 0.939 | 0.955 | 0.002 | 0.006 | 0.651 | 1.002 | 0.992 | 1.013 |
| Misdemeanor | -0.131 | 0.034 | 0.000 | 0.877 | 0.820 | 0.938 | -0.263 | 0.033 | 0.000 | 0.769 | 0.721 | 0.820 | 0.049 | 0.034 | 0.151 | 1.050 | 0.982 | 1.122 | 0.043 | 0.042 | 0.305 | 1.044 | 0.962 | 1.132 |
| Other Offense | 1.515 | 0.071 | 0.000 | 4.549 | 3.963 | 5.225 | -0.240 | 0.070 | 0.001 | 0.786 | 0.686 | 0.901 | -0.239 | 0.073 | 0.001 | 0.787 | 0.683 | 0.908 | -0.063 | 0.098 | 0.521 | 0.939 | 0.773 | 1.137 |
| Property Offense | 0.127 | 0.046 | 0.006 | 1.136 | 1.037 | 1.244 | -0.083 | 0.046 | 0.071 | 0.920 | 0.841 | 1.007 | 0.257 | 0.046 | 0.000 | 1.293 | 1.182 | 1.415 | 0.192 | 0.054 | 0.000 | 1.212 | 1.090 | 1.349 |
| Public Order Offense | -0.282 | 0.059 | 0.000 | 0.754 | 0.672 | 0.847 | -0.290 | 0.057 | 0.000 | 0.748 | 0.669 | 0.837 | -0.211 | 0.058 | 0.000 | 0.810 | 0.723 | 0.907 | 0.094 | 0.070 | 0.178 | 1.099 | 0.958 | 1.261 |
| Violent Offense (National) | 0.272 | 0.067 | 0.000 | 1.312 | 1.150 | 1.496 | -0.257 | 0.067 | 0.000 | 0.773 | 0.679 | 0.881 | -0.086 | 0.067 | 0.204 | 0.918 | 0.804 | 1.047 | 0.161 | 0.081 | 0.048 | 1.174 | 1.001 | 1.377 |
| County 2 | -0.527 | 0.038 | 0.000 | 0.590 | 0.548 | 0.636 | -0.006 | 0.038 | 0.865 | 0.994 | 0.922 | 1.070 | 0.553 | 0.039 | 0.000 | 1.738 | 1.610 | 1.875 | 0.502 | 0.047 | 0.000 | 1.652 | 1.507 | 1.812 |
| County 3 | 0.057 | 0.078 | 0.461 | 1.059 | 0.909 | 1.234 | 0.451 | 0.085 | 0.000 | 1.569 | 1.330 | 1.855 | 0.329 | 0.079 | 0.000 | 1.389 | 1.189 | 1.623 | 0.123 | 0.091 | 0.179 | 1.131 | 0.944 | 1.351 |
| Male | 0.231 | 0.034 | 0.000 | 1.260 | 1.180 | 1.346 | 0.369 | 0.032 | 0.000 | 1.447 | 1.359 | 1.540 | 0.581 | 0.033 | 0.000 | 1.788 | 1.675 | 1.909 | 0.624 | 0.046 | 0.000 | 1.866 | 1.707 | 2.041 |
| $N_{individuals}$ | 7,160 | | | | | | 7,160 | | | | | | 7,160 | | | | | | 7,160 | | | | | |

*Notes*: All models were weighted using an inverse probability weight calculated from the results of the binary logistic regression model in Table B5.

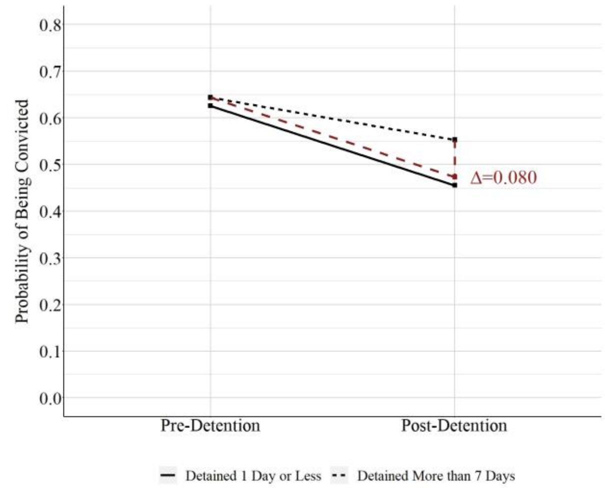
Panel A:

Failure to Appear*



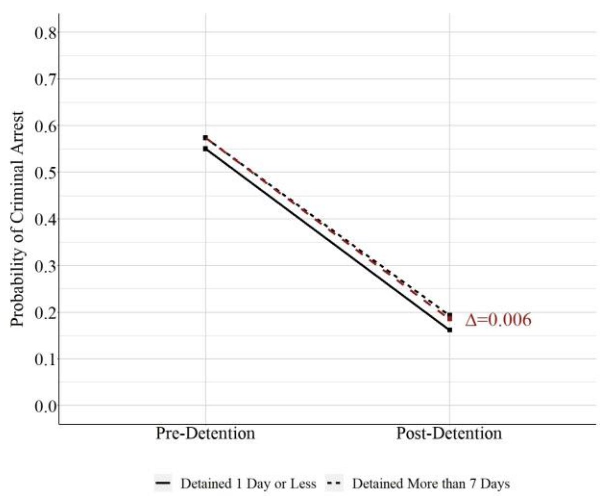

Panel B:

Convicted*




Panel C:

New Criminal Arrest




Panel D:

New Violent Criminal Arrest

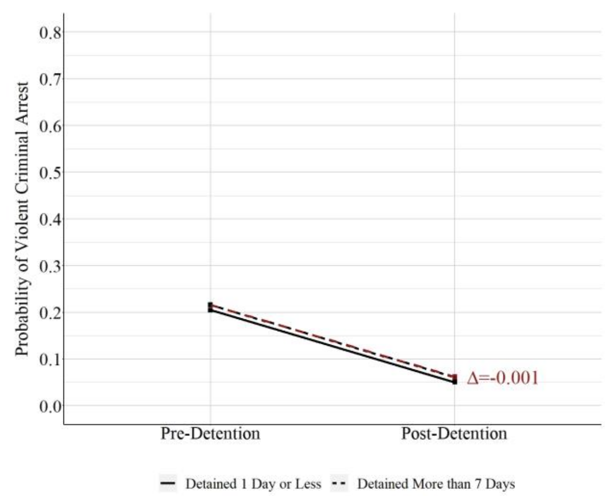


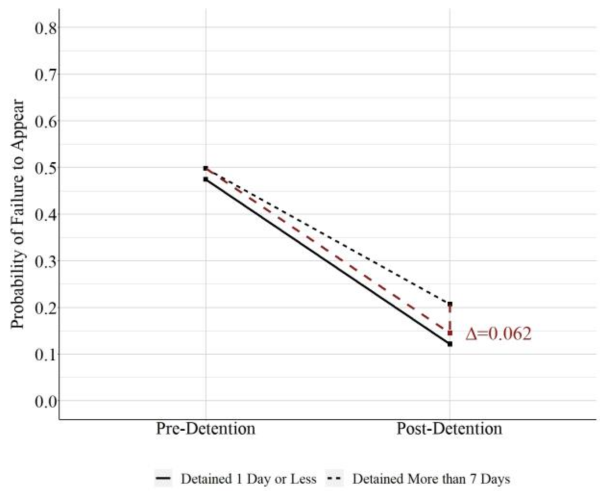

Figure C1. Plotted probabilities from doubly robust DiD model with only males ($N_{individuals}$ = 11,734; $N_{observations}$ = 23,468).

*Notes*: The model used to estimate the inverse probability weights and the doubly robust DiD models are provided in Tables C1 in Appendix C.

* Denotes differences were statistically significant at the $p < .001$ level.

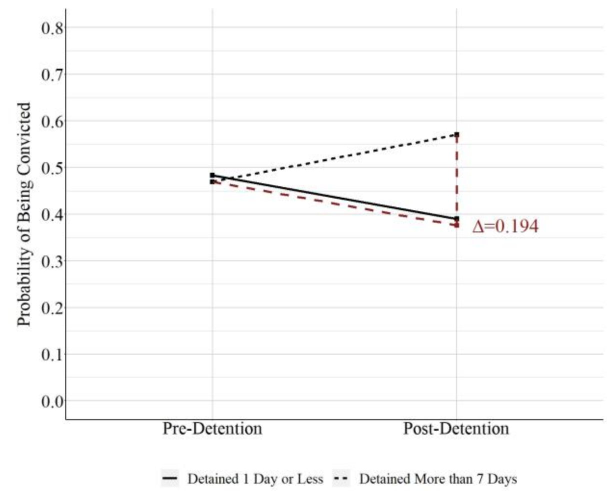
Panel A:

Failure to Appear*



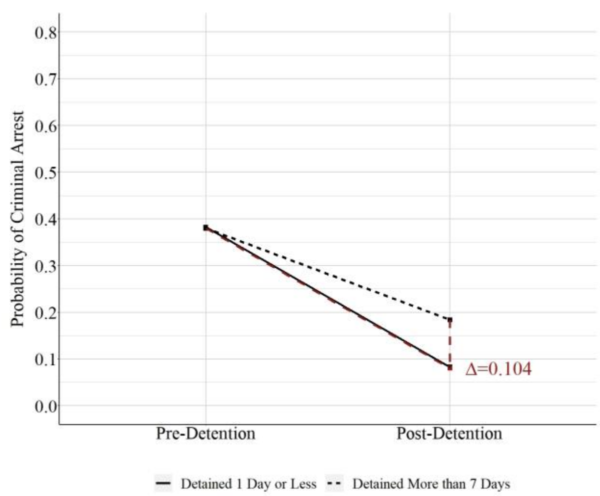

Panel B:

Convicted*




Panel C:

New Criminal Arrest*




Panel D:

New Violent Criminal Arrest

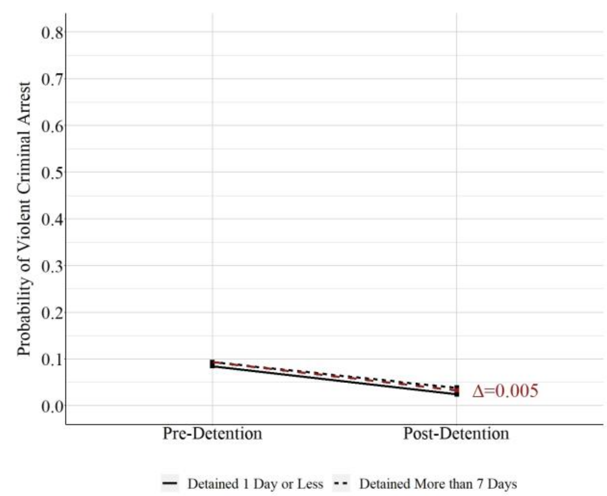


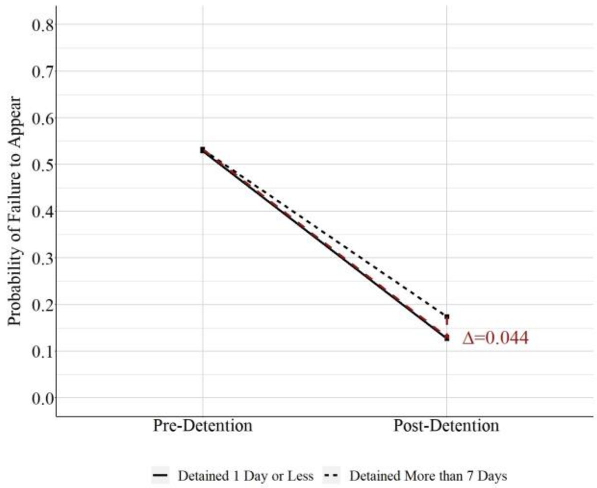

Figure C2. Plotted probabilities from doubly robust DiD model with only females ($N_{individuals}$ = 4,498; $N_{observations}$ = 8,996).

*Notes*: The model used to estimate the inverse probability weights and the doubly robust DiD models are provided in Tables C2 in Appendix C.

* Denotes differences were statistically significant at the $p < .001$ level.

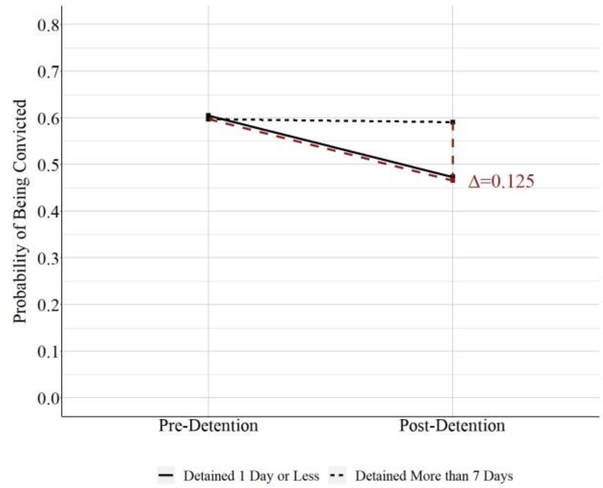
Panel A:

Failure to Appear*



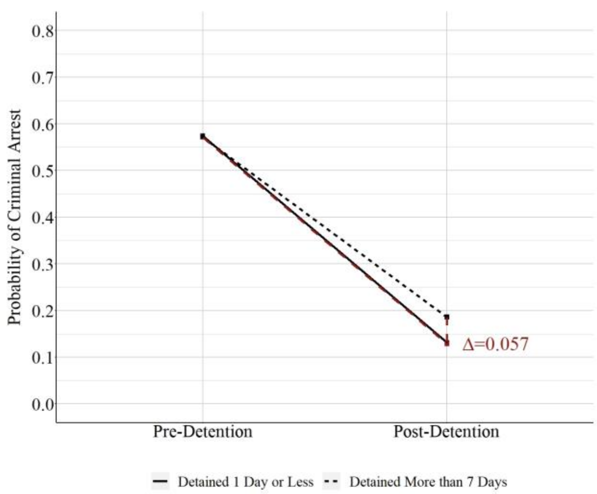

Panel B:

Convicted*




Panel C:

New Criminal Arrest*




Panel D:

New Violent Criminal Arrest*

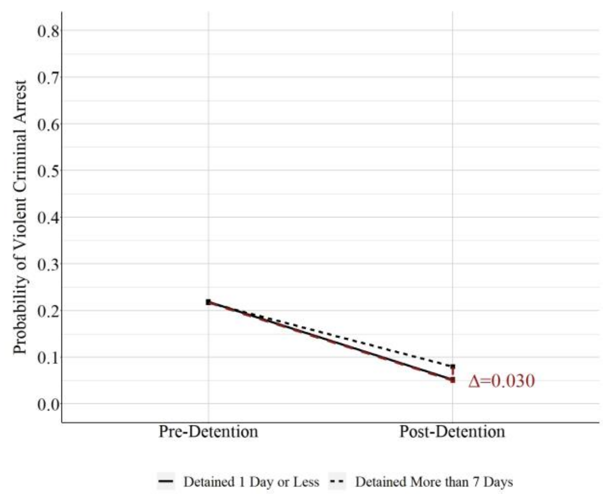


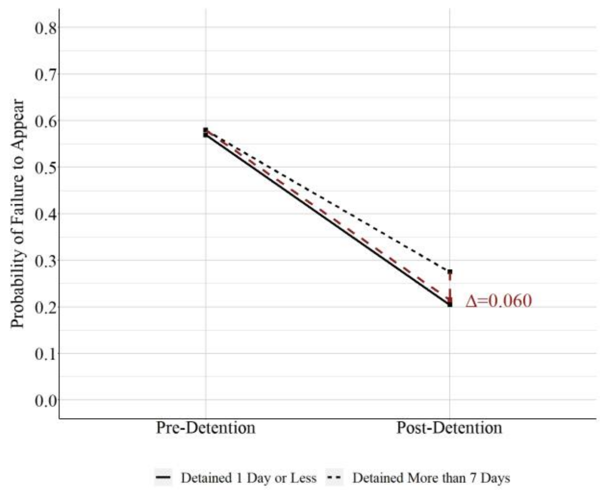

Figure C3. Plotted probabilities from doubly robust DiD model with only Whites ($N_{individuals}$ = 7,829; $N_{observations}$ = 15,658).

*Notes*: The model used to estimate the inverse probability weights and the doubly robust DiD models are provided Tables C3 in Appendix C.

* Denotes differences were statistically significant at the *p* < .001 level.

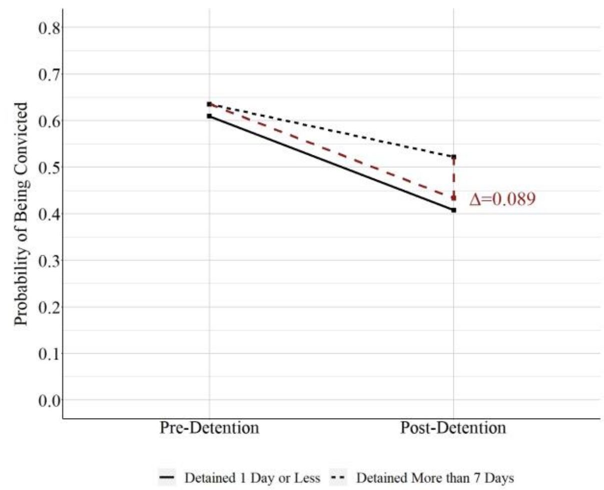
Panel A:

Failure to Appear*



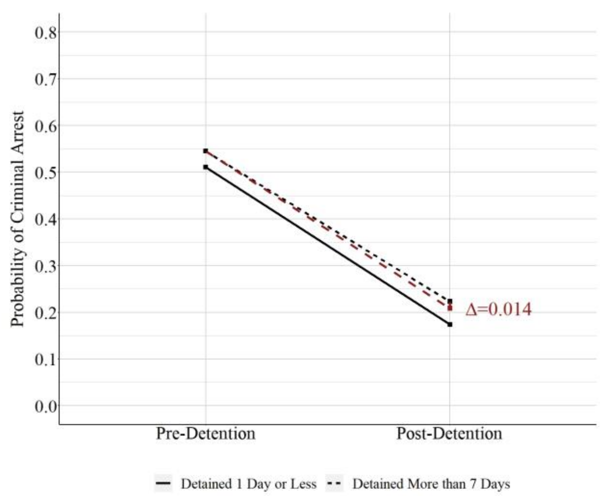

Panel B:

Convicted*




Panel C:

New Criminal Arrest




Panel D:

New Violent Criminal Arrest

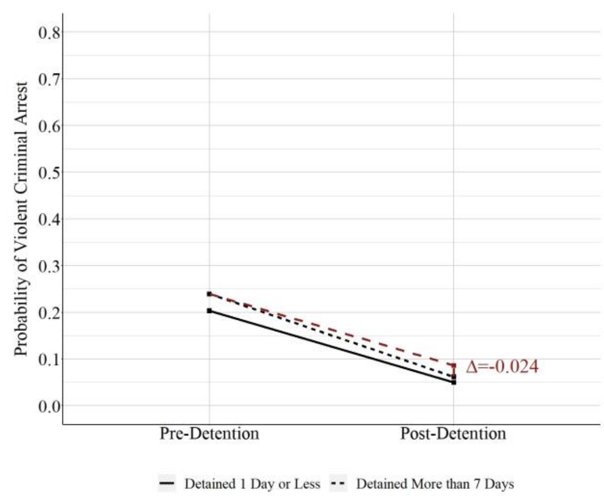



Figure C4. Plotted probabilities from doubly robust DiD model with only Blacks ($N_{individuals}$ = 7,160; $N_{observations}$ = 14,320).

*Notes*: The model used to estimate the inverse probability weights and the doubly robust DiD models are provided in Tables C4 in Appendix C.

* Denotes differences were statistically significant at the *p* < .001 level.