Estimating Prison Peer Effects: An Application of Local Instrumental Variables to Address Essential Heterogeneity in Social Interaction Effect Estimation

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ABSTRACT

This study examines prison peer effects in an adult prison population in the United States using a unique dataset assembled from the administrative databases of the Pennsylvania Department of Corrections and RAP sheets from the Pennsylvania State Police. A local instrumental variables estimation strategy is used to isolate causal prison peer effects in the presence of essential heterogeneity, which has been defined as bias due to selection on both levels and gains. Average prison peer effect estimates for rearrest and reoffending fail to reach significance, but evince essential heterogeneity. As a result, marginal prison peer effects due to cellmate social interactions vary; such that some inmates appear more likely to reoffend, while other appear less likely to reoffend after cellmate interactions. Crime-specific specifications shed light on one potential source of that essential heterogeneity: some crime-specific average prison peer effect estimates are substantial and negative, while others are substantial and positive. Potential implications for peer and prison effect estimates are discussed.

Keywords: social interactions, incarceration, causal effects, local instrumental variables, essential heterogeneity, peer effects, prison effects

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INTRODUCTION

This study isolates causal prison peer effects under essential heterogeneity for a sample of male, first-time releasees from Pennsylvania state prisons by examining the effect of cellmate interactions on reoffending. Essential heterogeneity can arise in the relationship between cellmate interactions and reoffending due to the combination of unobserved heterogeneity (one or more omitted variables) that influences reoffending directly and also indirectly, through interactions with the determinants of the type of cellmate interactions inmates have (Björklund & Moffitt, 1987; Manski, 2005; Heckman & Vytlacil, 1999; 2005; Heckman, Vytlacil, & Urzúa, 2006).

Instrumental variables techniques (Imbens & Angrist, 1994; Angrist, 2006; Bushway & Apel, 2010) that have previously been used to eliminate unobserved heterogeneity in the study of social interaction or peer effects (e.g., Fowler, 2009, 2012) cannot eliminate essential heterogeneity (Heckman et al., 2006). The local instrumental variables (LIV) method can (Heckman & Vytlacil, 1999; 2005). Moreover, the LIV method is designed to highlight heterogeneity and to isolate its sources (e.g., Basu, 2014). This study is the first to apply LIV to the study of social interaction effects in any context. The analysis highlights heterogeneity in marginal prison peer effect estimates, which contributes to null (or modest) prison peer effects.

Two literatures can benefit from the insights generated: the peer or social interaction effects literature and the prison effects literature. Social interaction effects are difficult to identify (Manski, 1993; Durlauf & Ioannides, 2010), with well-controlled studies often yielding modest (if any) effects (Gottfredson & Hirschi, 1990; Angrist, 2013). The social interaction literature has also generated inconsistent results, meaning effects pointing in both positive and negative directions for different samples using the same outcomes and for the same samples using different outcomes (Pratt et al., 2010; Sacerdote, 2011; Sacerdote, 2014). This study suggests a reason for those modest and inconsistent estimates: some individuals are affected positively through social interactions, some negatively. When all else is equal (i.e., when the samples balance, in parlance of propensity score matching), it makes sense that those positive and negative effects will average to zero, so it also makes sense that average treatment effect estimates are often near or nearly zero. When samples are unbalanced, those averages can bend in either direction, positive or negative, depending on the relationships studied to yield inconsistent results across samples and outcomes.

Similarly, the prison peer effect estimates generated by this study suggest why prison effect estimates may have been shown to be null or slightly criminogenic (Nagin et al., 2009), particularly in terms of the effect of time served on reoffending (Loughran et al., 2009; Snodgrass, Blokland, Haviland, Nieuwbeerta, & Nagin, 2011; Meade, Steiner, Makarios, & Travis, 2013). Time served is only one element of the prison experience; and it ignores heterogeneity in what happens to people while they are incarcerated. Prison experiences vary, such that social interactions within prisons vary. With respect to cellmates, some inmates encounter cellmates with more criminal experience than others. Even after attempting to account for this potential source of variation in prison peer effects in multiple ways, some response heterogeneity remains (Heckman, 2001; Loughran & Mulvey, 2010). It is, therefore, not unreasonable to suspect that other elements of the prison environment that can also be studied might exhibit variation in marginal treatment effects, which can lead to a similar pattern of canceling average effects (e.g., McGuinn, 2014).

This study begins with a discussion of the potential for the emergence of heterogeneous, rather than solely criminogenic, prison peer effects. To introduce both the terminology used and the prison context studied, data provided by the Pennsylvania Department of Corrections and the Pennsylvania State Police is described. The method, local instrumental variables, is then discussed. Prison peer effects are then estimated and discussed in the context of the peer and prison effect literatures.

THEORETICAL MOTIVATION

Social interactions between prison inmates have, currently and historically, been presumed to be mainly criminogenic, rather than crimino-suppressive, such that they are often blamed for the failure of prisons to reduce recidivism (Bentham, 1830; Clemmer, 1940, 1950; Gold & Osgood, 1992; Lerman, 2009; Nagin et al., 2009). Current arguments that "Prisons may provide for the transmission of information and skills that make individuals 'better' criminals" (Lerman, 2009, p. 154), echo Bentham's (1830) historical warning that "the indiscriminate association of prisoners" can lead to situations in which prisons "instead of places for reform" become "schools of crime" (§ VII). In their prominent review, Nagin et al. (2009) cited the schools of crime hypothesis as one of the primary explanations for their conclusion that prisons appear to have a "null or criminogenic" (p. 164) effect.

A plausible theoretical rationale for the presence of criminogenic prison peer effects invokes social influence through learning mechanisms. According to differential association theory, individuals' criminality, the underlying tendency to engage in criminal behavior, emerges and is through interactions with others who hold criminal values and have criminal skills that supplement their own (Sutherland, 1947). Ordinary learning processes such as dialogue, modeling, reinforcement, and punishment, propagate criminal behavior (Sutherland, 1947; Skinner, 1953;

Bandura, 1962; Burgess & Akers, 1966; Dishion & Dodge, 2005; Akers, 2009). The duration of peer associations moderates the effects learning processes exert, such that longer periods of time spent associating with peers increases peer effects (Agnew, 1991; Warr, 1993). Via developmental cascade theory (Masten et al., 2005), peer influence has been theorized to affect the life course for many years after the social interactions have occurred (Dishion, Veronneau, & Myers, 2010).

With respect to social interactions in prison, Clemmer (1940, 1950) built upon Sutherland's work, arguing that associating with other inmates leads to varying degrees of assimilation to the prison context via *prisonization*, a normative socialization process that, like differential association, is theorized to exacerbate criminality by instilling antisocial norms. He expected the ordinary learning mechanisms that support normative socialization outside prison to operate inside prison (Clemmer, 1940, 1950; Sutherland, 1947; Gold & Osgood, 1992; Jones & Schmid, 2000).

Clemmer (1950) also expected that prisonization would occur specifically through social interactions with cellmates. He predicted "a chance placement with a cellmate" (Clemmer, 1950, p. 317) to influence the development and degree of prisonization. Gold and Osgood (1992), who found that peer effects were most likely to arise between cellmates in the juvenile facilities in Michigan, confirmed Clemmer's (1940) prediction that cellmate associations engender criminality.

But, prison peer effects need not be criminogenic. They can also be crimino-suppressive. In contrast to previous peer influence theorists, McGloin (2009) argued that whether offending increases or decreases after social interactions depends on the relative distance between the criminality and criminal experience of the interacting peers. Using the AddHealth data, she found that paired peers moderate toward each other in terms of their delinquency: more delinquent peers became less delinquent, while less delinquent peers became more delinquent.

McGloin's (2009) balance theory can be applied to the prison context, where criminality varies, even among inmates (Clemmer, 1940, 1950, p. 319). In the prison context, balance theory yields the expectation that prisoners in dyadic associations will moderate toward each other in terms of the criminal attitudes they adopt and the criminal behaviors in which they engage. Inmates with lesser criminality or criminal experience than their cellmates will experience criminogenic effects, whereas inmates in possession of more criminality and criminal experience than their cellmates will experience crimino-suppressive effects.

An analytic limitation that arises in the prison context is that not all prisoners are released, which means post-prison offending cannot be examined for all inmates. Still, some expectations regarding the offending behavior of released prisoners after cellmate interactions can be drawn on the basis of balance theory. If, on average, released prisoners moderate toward their cellmates in terms of their reoffending behaviors, inmates who have cellmates with more generalized criminal experience should commit more crimes. For example, inmates whose cellmates had previously been incarcerated should commit more crimes than inmates who cell with other first-time inmates (Clemmer, 1950; Schrag, 1954).

Generalized outcomes, such as rearrest or reincarceration for any crime, may obscure important heterogeneity with respect to the types of crimes that can be committed. Theoretically, different types of crimes may have different situational etiologies even if a single factor (i.e., self-control) explains much of the motivation to commit crime (Sutherland, 1947; Cornish & Clarke, 1985; Gottfredson & Hirschi, 1990; McGloin & Shermer, 2009). Failing to account for crime type heterogeneity may, therefore, leave considerable uncontrolled variation in the relationship between cellmate criminal experience and reoffending.

Heterogeneity in offending has been explored empirically by examining reinforcing and switching effects (Bayer, Hjalmarsson, & Pozen, 2009), the presence of which comports with the expectations of balance theory. With respect to switching effects, inmates who have never committed a particular crime who have cellmates who have committed that crime, should be more likely to commit that crime than inmates who have cellmates who have not committed that crime. For example, if an inmate who has never committed a robbery interacts with a cellmate who has committed a robbery, the implication is that the inmate who had previously never committed a robbery will be more likely to do so. Finally, with respect to reinforcing effects, inmates who have committed a particular crime who then have cellmates who have also committed that crime, should be more likely to commit that crime than inmates who have cellmate who have never committed that crime (Bayer et al., 2009).

In the single published study that examined social interaction effects in an incarcerative environment, Bayer et al. (2009) found that delinquents housed in juvenile correctional facilities with other delinquents who had committed similar offenses were more likely to persist in committing those offenses after their release. They found no evidence that the delinquents began to commit new offenses after being housed with other delinquents. In sum, they found reinforcing, but not switching, criminogenic prison peer effects for some crime types, including drug offense, petty larceny, aggravated assault, and felony sex crimes. Although this direct evidence of prison peer effects is sparse, it supports the notion that prison peer effects are, on average, criminogenic rather than crimino-suppressive.

The current study distinguishes itself from Bayer et al. (2009) in several ways. The study sample consists of adult prisoners in the United States. Dyadic cellmate associations, rather than facility-level effects, are explored (McGloin, 2009). And, heterogeneity in prison peer effects is investigated via the exploration of marginal prison peer effects, rather than focusing mainly on average prison peer effects.

DATA

The Pennsylvania Department of Corrections (PADOC) and the Pennsylvania State Police (PSP) provided the data to investigate the question of whether prison peer effects are criminogenic or crimino-suppressive. A cohort of male *releasees*, who were admitted to PADOC custody for the first time on or after January 1, 2000 and released between January 1, 2006 and December 31, 2007, was selected and matched to their cellmates. Each releasee's longest-duration or *best cellmate* was then identified. The characteristics of the *cellmate pool*, which consists of all other cellmates with whom the releasee celled, were preserved. Record of Arrest and Prosecution (RAP) sheets for the releasees and each of their cellmates through mid-2012 were obtained from the PSP.

The 2006-2007 release cohort was chosen to allow for a four-year follow-up period, which comports with the prior literature that examines a three to five year follow-up period (Langan & Levin, 2002; Nagin & Snodgrass, 2013; Durose, Cooper, & Snyder, 2014). The first-time prison inmates in that cohort were isolated to eliminate the potential for prior prison commitments to condition the prison peer effects (Wheeler, 1961; Nieuwbeerta, Nagin, & Blokland, 2009). Double cellmates were chosen to examine core dyadic social relationships (Gold & Osgood, 1992; McGloin, 2009) and because a majority of PADOC inmates are double celled.[1] Since the first complete year of bed assignment data became available as of January 1, 2000, only those releasees who were admitted on or after that date were included in the final sample. Female inmates were also excluded from the current analysis.[2]

To organize the data by unique releasee-cellmate pairs, the best cellmate, defined as the cellmate with whom the releasee spent the most time in the fewest stretches was identified. A *stretch*

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[1] In 2000, 81% of the beds in the PADOC system were in double cells. By 2007, as the prison system expanded and after many single cells were converted into double cells, 90% of PADOC beds were in double cells.

[2] Females were excluded for several reasons. Firstly, female inmates are housed in different facilities, so they are not subject to the same institutional environments as male inmates. Females are also housed in only one tenth as many facilities, so there is far less variation in their housing environments. Finally, both preliminary analysis and preliminary reports from correctional officers suggested that social interactions with other inmates might affect female inmates differently. For instance, the correctional officers in both female facilities expressed the general sentiment that, "[t]he female population can be challenging to manage due to relationships that foster between inmates…problems…surface due to inmates consensually developing relations…that sour." For these reasons, social interactions amongst female inmates will be examined in future work.

is defined as a period of contiguous time spent double celled with a cellmate. Stretches that did not last at least one day were excluded. On average, 68.6% (SD=26.6, mode=75.9) of a releasee's *stay* is comprised of stretches.[3] The best cellmate was selected based on prior theory (Clemmer, 1940; Sutherland, 1947), which suggests that duration will intensify peer effects: all other things equal, the longest-duration cellmate association should theoretically exert greater prison peer effects (Agnew, 1991; Warr, 1993; Haynie, Giordano, Manning, & Longmore, 2005). Whether best cellmates exert greater influence than first, last, or any other individual cellmate is an empirical question not confronted by the current study.

Information from interviews, observations, and surveys of correctional personnel and inmates supplement the administrative data, which includes inmate and institution level data. The inmate data include demographic, criminal history (e.g., prior incarcerations), institutional history (e.g., misconducts and programming), and institutional testing (e.g., IQ and psychological) markers). Prison-level data include building, unit, and cell indicators, as well as structural information on cells (square footage, tier) and bed type (e.g., general and therapeutic).[4] To preserve the temporal ordering of the covariates for causal inference, the PADOC demographic, criminal history, and inmate testing data characterize cellmates and releasees based on the most updated information available at the time of the *first* pairing of the cellmate to the releasee.

To help to determine whether social interaction effects operate more strongly between pairs or groups of individuals (Urberg, 1992; Rees & Pogarsky, 2011), the average characteristics of the inmates with whom a releasee shared a double cell, excepting the best cellmate, were calculated. The time each cellmate spent with a releasee was used to weight these cellmate pool characteristics. In addition to the cellmate pool characteristics, distal effects are controlled by facility indicators, which account for fixed aspects of the environment that are common to all inmates housed in them (Manski, 1993; Fletcher, 2009, 2012).[5]

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[3] Although more than 90% of PADOC's beds are beds in double cells, inmates may spend time single celled (e.g., in the RHU) or they may be celled in dormitories, particularly if they are custody level two and near their release dates. Inmates may also leave PADOC SCIs to face charges in court. In that case, they might be in a county facility for months at a time (personal communications, 2015).

[4] Assignment to a bed designated for a therapeutic community, for example, is an indicator of time spent in drug and alcohol programming. Data beyond bed status on programming received is not currently available, although it may be in the future.

[5] In principle, building and unit-level fixed effects could be employed as well. However, with hundreds of buildings and units throughout the PADOC system, the unique releasee-cellmate paired sample could not support such an analysis.

The final analytic sample includes 10,116 unique release-cellmate pairs.[6] The durations of the best cellmate associations range in length from 1 to 2,079 days, with a mean of 181.3 days and a standard deviation of 144.4 days. Summary statistics appear in Table 1.

Crime Types

To examine criminal offending and the potential for skill transfer at a finer level than reincarceration and rearrest, the charges reflected on the arrest records of the releasees and their cellmates were delineated into crime types using two different categorization schemes. In the first (*Type P* crimes), the crimes were organized into eight categories according to how they are delineated in the Pennsylvania Criminal Code, the Controlled Substances, Drugs, Devices, and Cosmetics Act, and Pennsylvania's Motor Vehicle Code. In the second (*Type Q* crimes), the crime types were further divided into forty different categories, based on their literals. The crime type delineations and the prevalence of releasee and cellmate offending within each are summarized in Table 2. Crimes included within each type are presented in Appendix C.

Outcome Variables

The dichotomous outcome variables include: reincarceration within four years, rearrest within four years, and rearrest for specific crime types within four years. In the four years post incarceration, 4,684 (46.30%) of the releasees had been reincarcerated at least once, while 5,214 (51.54%) releasees had been rearrested. However, nearly one quarter (n=1,134, 24.2%) of the reincarcerated releasees had not been rearrested prior to their reincarceration.

Treatment Variables

The treatment variables are binary characterizations of the best cellmate's prior criminal history. The first, which indicates whether the best cellmate had previously been incarcerated in PADOC, is intended to measure whether cellmates exert a generalized criminogenic influence on releasee reoffending (Clemmer, 1940, 1950). Multiple measures of whether best cellmates have specific crime types in their prior criminal histories are intended as more nuanced measures of criminogenic influence. In combination with the releasee's prior criminal history, the latter variables are intended to detect evidence of switching and reinforcing behaviors (Bayer et al., 2009). If the best cellmate has experience with a particular crime type, while the releasee does not, switching effects are possible. If both have experience with a particular crime type, reinforcing effects may

[6] Twenty-six pairs in two facilities were dropped because there were too few pairs in those facilities to support analysis. The two facilities were SCI-Pittsburgh, which was closed during much of the period between 2000 and 2007 and SCI-Waymart, which closed in 2003.

emerge. In combination, they are akin to relative measures, advocated by McGloin (2009). Prior cellmate offending by arrest crime type appears in Table 2.

Instrumental Variables

The instruments included in the choice model are: the percentage of available beds in the prison that are on the unit to which the releasee and cellmate were first assigned; whether the releasee and cellmate are of the same race; whether the releasee and the cellmate were convicted in the same county; and the amount of time the cellmate had been incarcerated prior to assignment to the releasee. Together, the instrumental variables account for different aspects of the bed assignment process which are, respectively, bed availability, the prisons' preference for pairing people of the same race, inmates' tendency to associate with other inmates from the same general area,[7] and a pseudo-random element of the bed assignment process.[8]

For valid causal inference, the instruments must impact releasee reoffending only through the cellmate assignment process. Each of the instruments, in addition to belonging in the cellmate assignment choice model, should not belong in the reoffending outcome model. The potential for lack of bed availability (i.e., overcrowding) to affect reoffending has been explored (and reviewed) in the empirical literature, which has uncovered little evidence of a direct impact (Farrington, 1980; Gaes, 1985). It is, therefore, plausible that bed availability affects reoffending only by limiting the cellmates to which an inmate can be assigned.

In the case of each of the other instruments, it is reasonable to presume that the cellmate social interactions are the conduit through which they affect releasee rearrest and reincarceration because the instruments are artifacts of the pairing. The best cellmate's time in prison until pairing and whether the releasee and the cellmate are of the same race and were convicted in the same county can only be relevant to release outcomes once the dyad is created and social interaction has begun. However, there are theoretical reasons why race and county of origin might be construed to independently impact reoffending.

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[7] Interviews with inmates and correctional personnel revealed that it is not uncommon for inmates to have met their cellmates in county jails. In additionally, being from the same town or neighborhood is also often enough to spark an initial conversation, which may lead to association that results in a cell request. The binary measure that reflects whether a releasee and his cellmate were committed from the same county attempts to account for these possibilities.

[8] With respect to instrumentation in the local instrumental variables method, Basu et al. (2007) write, "If there are multiple instruments which have been proven to be significant determinants of the choice of treatment, then all of them should be simultaneously included in the estimation of the choice model" (p. 1155). This is because different instruments estimate different treatment effect parameters. Each of these instruments is not valid in every model, so as many of them as are valid within a particular model are included, as the analytic results in Tables 9-11 indicate.

Prison gangs are typically delineated on racial lines and can propagate offending from the prison to the street and back again (Pyrooz, Decker, & Fleisher, 2011; Skarbek, 2014). Similarly, individuals need not be gang-involved to co-offend after meeting in prison, although they do need to be proximal (Reiss, 1988; Roxell, 2011). Nevertheless, each of those hypotheses relies on social interactions: individuals must meet and interact in order to reoffend in concert, whether through gang involvement or co-offending. This study isolates a particular kind of social interaction: between cellmates. Therefore, cellmate interactions are the intermediaries through which prison peer effects are generated.

Even if gangs and co-offending do influence outcomes, they are likely to have only very small effects because they are likely to influence outcomes only for a very small number of releasees. During the time period covered by this study, Fleisher and Decker (2011) reported that PADOC had identified only about 2,400 gang members (about 0.05% of the prison population). The potential to interact with gang members in PADOC is, therefore, very limited.[9] With respect to the potential for post-prison co-offending, Roxell (2011) found that only 2% of formerly incarcerated inmates in Sweden appeared to co-offend post-release, and Reiss (1988) reported that co-offending is rare in adulthood, as most adolescents desist and older offenders become more efficient criminals. To bolster the arguments that the included instruments are strong and exogenous to the outcome model, statistical tests of their validity and exogeneity are presented in Tables 4, 6, and 8 (Bound, Jaeger, & Baker; 1995; Stock & Yogo, 2005; Baum et al., 2007).

Covariates

As described above, inmate-related covariates include demographic information, institutional history and testing data, and criminal history information. Contextual variables (e.g., facility fixed effects, cell tier) are supplemented by variables that index quarter of release and variables that further characterize the releasee-cellmate association. Table 1 presents summary statistics for all covariates.

CONCEPTUAL AND METHODOLOGICAL FRAMEWORK

The underlying process that creates a criminogenic cellmate association is a binary decision: whether or not two inmates with differential criminal backgrounds cell together. The differentiating

[9] In addition, the inmates interviewed (n=24) specifically reported a lack of gang culture because it is not respected. They talked about individuals "holding they own" and how "Philly ain't about gangs" (personal communications, 2015). Only one inmate seemed to be more regularly involved with more organized forms of criminal activity, as opposed to operating and defending a drug corner (e.g., Simon & Burns, 1997). However, he, too, derided the "peacocking" (i.e., showboating) culture associated with gang members (or guys posing as gang members) in PADOC.

characteristics of cellmate associations are characteristics of the inmates that that reflect their criminal experience (e.g., prior incarcerations and arrests for specific crime types). The social interactions that emanate from celling decisions are expected to be implicated in inmates' recidivism outcomes. This framework, instead of answering the question of what happens when two inmates interact, answers the question what happens when two differentially experienced inmates interact?

Identifying whether interactions between social actors produce measurable, causal peer effects is a notoriously difficult statistical estimation problem that requires consideration of endogenous selection into social associations, reciprocity in the outcomes proceeding from those associations, and contextual influences on those outcomes (Manski, 1993). In observational social interaction studies across disciplines, the simultaneous nature of social relationships has generally gone unaddressed, as have the selection biases and contextual effects that contaminate estimates of social interaction effects (Gottfredson & Hirschi, 1990; Manski, 1993, 2000; Mouw, 2006; Gangl, 2010; Durlauf & Ioannides, 2010; Angrist, 2013; Sacerdote, 2014). Even in well-controlled studies, however, social interaction effect estimates have proven, at best, modest and heavily context-dependent (Hartup, 2005; Mouw, 2006; Gangl, 2010; Horney et al., 2012; Angrist, 2013; Sacerdote, 2014). The current study provides insight into why well-controlled studies of social interactions have generally produced only meager evidence of their effects (Osgood & Briddell, 2006; Angrist, 2013): average treatment effects estimated for high-level outcomes obscure important response heterogeneity (Nagin, 1999; Heckman, 2001; Heckman & Vytlacil, 2005; Loughran & Mulvey, 2010). Estimates based on unbalanced samples may exacerbate that problem.

Response heterogeneity implies that observationally equivalent subjects appear to be affected differently by observationally equivalent treatments (Heckman, 2001; Loughran & Mulvey, 2010). One reason effect estimates might display response heterogeneity is that outcomes generated by treatments are affected by factors about which researchers have little or no information: there are omitted variables. That this *unobserved heterogeneity* or *selection on levels* plays a role in outcomes is canonical (Heckman, 1976; Heckman & Singer, 1984; Wooldridge, 2006).

That selection on levels is only one source of potential bias emanating from the unobserved determinants of outcomes is less well established (Björklund & Moffitt, 1987; Manski, 2005; Heckman, Urzúa, & Vytlacil, 2006). The phenomenon whereby decisions are made based on the outcomes they are expected to yield is called *selection on gains*. Expectations on the part of decision makers regarding the outcomes of treatment are also typically unobserved by the researcher (Moffitt, 2001; Manski, 2005; Heckman et al., 2006; Brave & Walstrum, 2014).

Heckman et al. (2006) call response heterogeneity that results from a combination of selection on levels and selection on gains *essential heterogeneity*. Heckman and Vytlacil (1999, 2005) demonstrate that analytic techniques that eliminate biases due to selection on levels do not eliminate biases due to selection on gains. The estimates generated through these analytic techniques either remain biased or apply only to a small portion of the sample under study (Heckman & Vytlacil, 2005; Heckman et al., 2006; Basu, Heckman, Navarro-Lozano, & Urzúa, 2007; Heckman & Urzúa, 2010).

The Empirical Model[10]

To make the problem clearer in the current prison peer effect framework, consider the following regression notation, which represents one of the core causal prison peer effect relationships to be understood:

$$rearrest_r = \alpha + \beta pinc_c + \gamma x_{rcptf} + u_{rcptf}$$

Cellmate prior incarceration ($pinc$) is theorized to affect releasee $rearrest$, which also depends on the characteristics of the releasee (r), his cellmate (c), his cellmate pool (p), defined as the cellmates with whom the releasee celled, contextual and timing characteristics (t), such as the timing of the releasee's release, and facility fixed effects (f).

Bias due to selection on levels may enter the preceding model if releasees vary in their motivation to desist from or persist in crime. Given equal probabilities of arrest, releasees who are motivated to persist in crime are more likely to be rearrested than releasees who are motivated to desist from crime. These motivations (mot) toward or away from continued criminal behavior are unobservable in the data, but may influence outcomes. They can be represented as such:

$$rearrest_r = \alpha + \beta pinc_c + \gamma x_{rcptf} + \delta mot_r + u_{rcptf}$$

Bias due to selection on gains can enter this relationship if the releasee's motivation to persist on a criminal path also motivates him to cell with a cellmate he perceives as able to, for example, broaden his criminal connections (Skarbek, 2014), increase his criminal skills (Clemmer,

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[10] This discussion borrows heavily from Heckman and Vytlacil (1999, 2005), Heckman et al. (2006), and Brave and Walstrum (2014). Reference Heckman and Vytlacil (1999, 2005) and Heckman et al. (2006) for detailed descriptions of the econometrics. The empirical model is estimated using the *margte* command in STATA 13 (Brave & Walstrum, 2014).

1940), or enhance his criminal capital (McCarthy & Hagan, 2001). Alternatively, a releasee who is motivated toward desistance may be interested in celling with a cellmate whom he perceives to be a more stabilizing, prosocial influence (Giordano, Cernkovich, & Randolph, 2002; personal communications, 2015). In either case, the releasee's motivation influences his cellmate association decision as well as his reoffending outcomes:

$$rearrest_r = \alpha + \beta pinc_c + \gamma x_{rcptf} + \delta mot_r + \varphi(mot_r * pinc_c) + u_{rcptf}$$

This relationship, which displays essential heterogeneity (Heckman et al., 2006), is the relationship upon which the schools of crime hypothesis (Bentham, 1830) typically rests: inmates, whether of their own volition or as a result of the workings of the prison system, interact in ways that increase their tendencies to reoffend (Shaw, 1966, pp. 152-4; Gold & Osgood, 1992, p. 15; Dishion & Dodge, 2005, p. 397; Lerman, 2009; Mears, Stewart, Siennick, & Simons, 2013).

While it is possible eliminate bias due to selection on levels using ordinary instrumental variables techniques such as two-stage least squares (Imbens & Angrist, 1994) and while it is possible to strengthen the estimates from two-stage least squares by controlling for contextual effects (Fowler, 2009, 2012), it is not possible to eliminate the bias due to selection on gains with ordinary instrumental variables techniques (Heckman & Vytlacil, 2005; Heckman et al., 2006; Brave & Walstrum, 2014). Consideration of the previous equation reveals why: even in a two-step framework where instruments (z) are used to predict the decision to cell with a more criminally experienced cellmate, unobserved releasee motivation remains a predictor in both equations, so the error terms of the first and second stage equations remain correlated, thus violating a key instrumental variables assumption (Imbens & Angrist, 1994; Heckman & Vytlacil, 2005).

To estimate causal prison peer effects due to cellmate association when essential heterogeneity may be present, the decision to cell with a more or less criminally experienced cellmate must be modeled explicitly, a process that necessitates a two-stage framework. Fortunately, the conceptual framework outlined above is also a two-stage framework. In the conceptual framework, two processes sequentially determine releasee reoffending: a binary decision-making process that determines whether a releasee is celled with a cellmate who has more or less criminal experience (e.g., a prior incarceration record) and the subsequent process of ongoing social interaction that produces reoffending. Local instrumental variables (LIV) is a two-stage analytic framework that comports with the conceptual framework. LIV also enables causal treatment effect identification under essential heterogeneity.

The local instrumental variables method extends the potential outcomes framework (Fisher, 1935; Cox, 1958; Rubin, 1978) of the Roy (1951) model to situations in which essential heterogeneity is endemic (Heckman & Vytlacil, 1999, 2005). The seminal Roy (1951) model characterized a two-sector labor market participation decision and the outcomes of that decision (Heckman & Vytlacil, 1999; Heckman & Vytlacil, 2005). As such, it is easily adapted to the current framework, wherein assignment to a more criminally experienced cellmate, relative to a less criminally experienced cellmate, is theorized to engender criminogenic effects on reoffending (Clemmer, 1950; Sutherland & Cressey, 1955; McGloin, 2009).

Heckman and his colleagues (Heckman & Vytlacil, 1999, 2005; Heckman et al. (2006)) developed the LIV method, which Brave and Walstrum (2014) implemented for STATA in the *margte* command. As applied here, *margte* assumes normality and estimates a first-stage equation that relies on instruments (z) to achieve identification. In ordinary IV strategies, such as two-stage least squares, the first-stage estimates are fed directly into the second stage outcome equation (Imbens & Angrist, 1994; Angrist & Pischke, 2009). In LIV, the choice model predicts the probability of being celled with a more criminally experienced cellmate based on the available data. This probability is referred to as the *propensity score*. The propensity score then becomes the main independent variable in the second-stage outcome model that predicts reoffending.

The reoffending outcomes estimated as a function of the propensity score are not prison peer effects. To calculate the prison peer (i.e., treatment) effects, the derivative of the predicted outcome equation is taken with respect to the propensity score. This derivative is the local instrumental variable to which the name of the method refers (Heckman et al., 2006, p. 397).

As is the case with post-estimation of categorical dependent variable models, the marginal prison peer effects are calculated at particular levels of the covariates (Long, 1997; Basu et al., 2007), generally means, and across the range of the propensity score (Heckman et al., 2006). Marginal prison peer effect estimates are expressed in terms of the propensity <u>not</u> to be treated, which means the collective contribution made to the outcomes by unobserved factors, typically abbreviated U_D, can be quantified (Heckman et al., 2006). Thus, marginal prison peer effects can be increasing or decreasing with respect to an individual's probability of being treated. The returns to cellmate criminal experience vary for different individuals (Björklund & Moffitt, 1987; Heckman, 2000). To get average prison peer effects, Heckman et al. (2006) show that one need only integrate over the marginal prison peer effects with respect to the propensity to cell with a cellmate who does not have a prior incarceration (i.e., the propensity not to be treated or U_D).

The Language of Marginal Treatment Effects

The preceding outline of the local instrumental variables method foreshadowed the somewhat difficult language of marginal treatment effects, which bears a short introduction. What does it mean for effects to be increasing (or decreasing) in the probability of being treated? Or, for that matter, what does it mean for effect to be increasing in the probability of not being treated? What are these unobservables? Returning to the motivating model helps to clarify.

$$rearrest_r = \alpha + \beta pinc_c + \gamma x_{rcptf} + \delta mot_r + \varphi(mot_r * pinc_c) + u_{rcptf}$$

Were the u_{rcptf} absent from the preceding equation, mot_rwould be the only observed factor; and it would be generating differential rearrest probabilities through differential celling probabilities. Decreasing marginal prison peer effects on rearrest with respect to the increasing influence of criminal motivation, then, means that the releasees who are least motivated to cell with cellmates with prior incarcerations are also least likely to be rearrested in the four years post-release. Inmates who are most motivated to cell with criminally experienced cellmates are also most likely to be rearrested during the four-year follow-up. In short: inmates who want to persist in their criminal lifestyles will enter into cellmate associations that help them meet that goal (Bentham, 1830; Shaw, 1966; Nagin et al., 2009).

It is important, however, not to commit to motivation as an explanation of the estimated prison peer effects or even to frame mot_r as if it could be distilled into a single dimension. The unobservables are likely many, particularly when the motivation of other actors, such as cellmates and correctional personnel, are among the unobserved determinants of the decision to cell with a criminogenic cellmate. (There is more discussion on this point in the following section.) For example, releasees might end up celling with cellmates with prior prison experience because older inmates are occupying the majority of bottom bunks, so only top bunks are available for younger, less experienced inmates (personal communication, 2015); or an inmate might have a hard time "keeping a cellie," so his unit manager might cell him with a more experienced inmate to "chill him out" (personal communications, 2015); or, it might be that the cellmate wants to mold the first-timer in his image (e.g., Earley, 2000). The possibilities are multitudinous. While the u_{rcptf} must be considered to understand response heterogeneity in prison peer effects, characterizing them can be tricky, misleading business.

Understanding response heterogeneity in prison peer effects requires an understanding of the tradeoffs between what is known and what is unknown in the production of marginal prison peer effects between cellmates. Where marginal prison peer effects are estimated, the influence due to the unobservables, u_{rcptf} (or U_D) is balanced by the influence of the observables, x_{rcptf}(or, simply, X); the propensity to be treated is balanced by the propensity not to be treated. Hence, the releasee is indifferent between celling with and not celling with a more (rather than less) criminally experienced cellmate.

Identifying Assumptions

Heckman and Vytlacil (1999, 2005) detailed the assumptions that must be met to identify an LIV model. They include Imbens and Angrist's (1994) first and third instrumental variables assumptions (but not the second); Cox's (1958) stable unit treatment value assumption (SUTVA); Rosenbaum and Rubin's (1983, 1984) criterion that the propensity score be supported; and other standard assumptions that ensure that the probability of treatment and the outcomes are well-defined and that integration is possible over the mufti-dimensional unobservables. In the current implementation, normality is also assumed to parametrically identify the effects (Brave & Walstrum, 2014). Appendix A details these assumptions.

The assumption most likely to be violated by the current analysis is the stable unit treatment value assumption. SUTVA has the potential to be violated for at least two reasons. The first is that some releasees share the same best cellmate. The second is that the releasees are not solely responsible for celling decisions. Upon consideration of the prison context, however, neither emerge as major concerns.

About 17% (n=1,699) of the releasees share the same best cellmate. To violate SUTVA, the first releasee would need to provide second releasee with information about the cellmate's criminal background that the second releasee does not already have. This is unlikely in prison, where the crimes for which other inmates have been convicted are generally known, and known quickly (Clemmer, 1940; Sutherland & Cressey, 1955, p. 505; personal communications, 2015).

PADOC inmates reported receiving information about other inmates' criminal histories from correctional officers, other inmates, and through friends and family members on the outside who can search the Internet for background information on other inmates (personal communications, 2015). It is highly unlikely that inmates will self-select into cellmate associations without knowing a potential cellmate's criminal background (personal communications, 2015).[11] In particular, it is well known that inmates eschew celling with sex offenders, particularly child molesters, and other inmates (i.e., snitches) whose past behavior strikes them as abnormal (Schrag, 1954; Akerstrom, 1986; Tewksbury, 2012). This is true of PADOC prisoners as well (personal communications, 2015). This potential source of a SUTVA violation is, therefore, obviated by the prison context.

The more serious potential SUTVA violation emerges from the nature of social interactions: they are not one-sided decisions. Whereas the local instrumental variables framework assumes a single decision-maker, by definition social interactions take place between at least two people. At a minimum, the releasee and his cellmate must (at least tacitly) agree to cell together. That decision-making process is further complicated by the oversight of prison personnel, who have the latitude to override inmate preferences.

To avoid violating SUTVA, the releasee must be assumed to have the final say in the celling decision. This assumption is not unreasonable because the releasee can exercise at least one ultimate option that allows him to end and/or avoid cellmate associations he does not want: he can go to the hole (i.e., solitary confinement). To get sent to the hole, an inmate can attack his cellmate, refuse to obey an order to cell with someone, or ask to enter protective custody (personal communications, 2015). For this reason, the final celling decision rests with the releasee: SUTVA can hold.

ANALYSIS AND RESULTS

The analysis proceeded in several stages. Linear probability models were estimated to establish whether cellmate criminal experience appeared to affect releasee reoffending outcomes (Angrist & Pischke, 2009). Two-stage least squares estimates helped to establish the viability of the instruments (Imbens & Angrist, 1994; Stock & Yogo, 2005; Baum, Schaffer, & Stillman, 2007). Tests for essential heterogeneity were performed (Heckman et al., 2006), and then the marginal and average treatment effect estimates were generated (Brave & Walstrum, 2014). Probit models with endogenous regressors (*ivprobit*) and semiparametric LIV specifications were estimated for some outcomes to explore the results.

Preliminary Analyses: Linear Probability and Two-Stage Least Squares Models

Rearrest and reincarceration models. The rearrest and reincarceration linear probability models investigate whether celling with a best cellmate who has a prior prison record increases a

[11] Many of the twenty-four inmates interviewed reported "showing papers," meaning sharing their court documents with each other. Upon placement with a new cellmate, an inmate might immediately ask to see his cellmate's papers. Unwillingness to show papers creates suspicion about one's background (i.e., that it includes sex offenses).

releasee's probability of being rearrested or reincarcerated for any offense. Estimates for the relationship between cellmate prior incarceration and releasee rearrest and reincarceration are presented in Table 3. Seven models were estimated, into which the treatment variable, instruments, and covariates were sequentially added.[12] The results suggest that there might be a positive relationship between cellmate prior incarceration and releasee rearrest because the coefficient on rearrest consistently hovered around 0.030 and remained significant at p=0.01, even after all covariates were added. Cellmate prior incarceration and releasee reincarceration, although also appearing consistently positively associated, were not significantly related in any of the models.

Table 4 presents estimates from two-stage least squares. Note that the estimates differ markedly from the LPM specifications. The coefficient estimates for cellmate prior incarceration, which were positive in the LPMs for both outcomes, are now negative. Neither is significant, but the coefficient on cellmate prior incarceration in the reincarceration model is now approaching significance, whereas it is not for rearrest. Table 4 also presents the results of the tests of the instruments, which should be interpreted with caution due to the dichotomous nature of the outcomes. They show that the models are identified, that the instruments are, indeed, instruments, and that they are not weak (Bound et al., 1995; Stock & Yogo, 2005; Baum et al., 2007).

Switching models. The switching models examine whether releasees are more likely commit crimes they have never committed after celling with best cellmates who have committed those crimes. Models explored all forty-eight crime types listed in Table 2. The LPM estimates for cellmate prior offending were significant at baseline only for the following offense types: public administration, drugs, and inchoate (Type P); and contempt, drugs, homicide, robbery, and weapons (Type Q). For all other offense types, cellmate experience with a particular offense type did not appear to be significantly related to releasee rearrest for those offense types. The instruments indicated to be strongest without violating the over- and under-identification tests varied, as indicated in Table 6, which presents the prison peer effect estimates. Strong instruments could not be found for public administration, inchoate, and weapons-related crimes, so LIV models for those outcomes were not estimated.

Reinforcing models. The reinforcing models presented in Table 7 examine whether releasees who have committed particular crimes are more likely to commit those crimes after celling with best cellmates who have also committed those particular crimes. The LPM estimates for

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[12] Groups of variables were added into the model in the following order: treatment, instruments, releasee characteristics, best cellmate characteristics, pool characteristics, time and contextual characteristics, facility fixed effects.

cellmate prior offending were significant at baseline for drugs, inchoate (mainly weapons, but also conspiracy and attempted crimes), person, and property offenses (Type P); and assault, drugs, kidnapping, motor vehicle theft, sexual assault, and weapons offenses (Type Q). As was the case with switching effects, the instruments indicated to be strongest without violating the over- and under-identification tests varied, as indicated in Table 8, which presents the prison peer effects estimates. Strong instruments could not be isolated for kidnapping, sexual crimes (even after conglomerating rape, statutory rape, and sexual crimes), or property offenses, so LIV models for those outcomes were not estimated. The models for person-based offenses failed to converge.

Essential Heterogeneity, Average, and Marginal Treatment Effects

Results of the Heckman et al. (2006) tests for essential heterogeneity appear in Table 12 for overall, switching, and reinforcing models. The tests look for differences in models specified sequentially with higher order propensity score terms and propensity score-covariate interactions. Significant likelihood ratio tests indicate the presence of essential heterogeneity. The tests for essential heterogeneity also provide a guideline as to what level polynomial should be specified in the LIV analysis. For example, if the likelihood ratio tests show that the model that incorporates a cubed term is significant over the one that incorporates a squared term, as is the case for switching drug crimes, a third-order polynomial is indicated.

Average and marginal prison peer effect estimates for the mean values of the covariates and tests for unobserved heterogeneity (i.e., selection on levels) are presented in Tables 9 through 11. Significant differences between the inverse Mills ratio among the releasees celled with more experienced (treated) and less experienced (untreated) longest duration (i.e., best) cellmates indicate the presence of selection on levels. Full output from some of the models appears in Appendix D. Marginal prison peer effects depend on the values of the propensity score and the covariates, so they are depicted graphically. Graphs depicting the estimated marginal and average prison peer effects for each model appear in the lower panes of Figures 1 through 14.

In a potential outcomes framework such as this, where D is the treatment, having a cellmate who has more criminal experience, and Y_1 are outcomes when the cellmate has more criminal experience, Y_0 are outcomes when the cellmate has less criminal experience, marginal prison peer effects ($MPPE$) are a function of both observed (X) and unobserved (U_D) information. They are reported in terms of U_D, the uniformly-distributed propensity not to be treated. The marginal prison peer effects thereby estimate effects in terms of the contribution to them made by the unobserved determinants of the treatment decision. Sloped marginal prison peer effects indicate the presence of selection on gains (Brave & Walstrum, 2014). Flat marginal prison peer effects indicate the absence of selection on gains, which should be confirmed by the Heckman et al. (2006) tests for essential heterogeneity.

$$MPPE(x, u_D) = E(Y_1 - Y_0 \mid X = x, U_D = u_D)$$

Average prison peer effects ($APPE$) are estimated by integrating over the marginal prison peer effects with respect to those unobserved treatment determinants, U_D.

$$APPE(X) = \int_0^1 \Delta^{MPPE}(x, u_D) \partial u_D$$

Switching and reinforcing prison peer effects amount to changes average and marginal prison peer effects as a result of the interaction of releasee and cellmate prior criminal experience.

Marginal switching prison peer effects ($SPPE$) may occur when:

$$SPPE \ = E[Y_1 - Y_0 \mid X_{rcptf} = x, U_D = u_D, C_r = 0]$$

where Y_1 are outcomes when the cellmate has previously committed a particular crime, Y_0 are outcomes when the cellmate has not committed that crime, the X_{rcptf} are the releasee, cellmate, cellmate pool, and contextual covariates, and $C_r = 0$, indicates that the releasee has not previously committed that crime. If releasees who have not committed a particular crime interact with cellmates with prior experience with that crime go on to commit that crime at higher rates than those who interact with cellmates who have not committed that crime, switching effects are indicated.

Marginal reinforcing prison peer effects ($RPPE$) may occur when:

$$RPPE \ = E[Y_1 - Y_0 \mid X_{rcptf} = x, U_D = u_D, C_r = 1]$$

where the Y_1, Y_0 and X_{rcptf} continue to have the meaning and $C_r = 1$, indicates that the releasee had previously committed that crime. If releasees who have committed a particular crime interact with cellmates with prior experience with that crime go on to commit that crime at higher rates than those who interact with cellmates who have not committed that crime, reinforcing effects are indicated. As is the case when prison peer effects are unconditioned, the marginal switching and reinforcing prison peer effects can be integrated over the U_D to obtain averages.

Rearrest and reincarceration effects. Where z are the instruments (percentage of open beds on the unit, cellmate time in prison before pairing, releasee-cellmate same race, and releasee-cellmate same conviction county) used to predict the treatment, $pinc_c$, which indicates whether the best cellmate has a prior incarceration, and p is the propensity score predicted after estimation of the choice model (i.e., the releasee's probability of having a best cellmate with a prior incarceration), the choice and outcome models for any releasee rearrest ($rearrest_r$) and any releasee reincarceration ($reincarceration_r$) within four years after release take the following forms:

$$pinc_c = \pi z + \gamma x_{rcptf} + \varepsilon_{rcptf}$$
$$rearrest_r |\ reincarceration_r = \alpha + \beta p + \delta x_{rcptf} + \varphi(p * x_{rcptf}) + u_{rcptf}$$

The interaction terms, $\varphi(p * x_{rcptf})$, represent the essential heterogeneity present in the estimated relationships. Marginal prison peer effects are calculated by taking the derivative of the outcome model with respect to p. Average prison peer effects can then be estimated by integrating over the MPPEs.

Table 9 reveals no significant average prison peer effects on rearrest or reincarceration after interactions with cellmates with prior incarceration records (relative to interacting with cellmates without prior incarceration records). However, in both of the outcome models the presence of selection on levels (i.e., unobserved heterogeneity) is indicated by the significant coefficients on the inverse Mills ratios (k) for both the treated and untreated cases (Appendix D) and the significant difference between the two ratios. The direction of the bias is such that the unobservables are negatively correlated with rearrest and reincarceration for releasees with cellmates who have a prior incarceration (positive coefficient on k) and positively correlated with rearrest and reincarceration for releasees with cellmates who do not have a prior incarceration (negative coefficient on k). For both, the graphical output indicates essential heterogeneity because the lines traced by the marginal prison peer effect estimates are not flat. However, the Heckman et al. (2006) tests indicate the presence of essential heterogeneity for reincarceration, but not for rearrest, as shown in Table 12.

The marginal prison peer effect heterogeneity in the graphs, therefore, is likely attributable to the unobserved heterogeneity revealed by the inverse Mills ratios.

The essential heterogeneity in the relationship between cellmate criminal experience, as indicated by prior incarceration, and releasee reoffending corresponds to substantial variation in marginal prison peer effects, despite imprecisely estimated average prison peer effects. Over the range of the propensity scores, the marginal prison peer effects for reincarceration, for example, range between a -50.83% decrease in the probability of reincarceration for the releasees least likely to pair with recidivist cellmates and an 37.53% increase in the probability of reincarceration for the releasees most likely to pair with recidivist cellmates. For rearrest, the corresponding range is similar between -50.83% and 36.86%. This prison peer effect heterogeneity, which indicates criminogenic effects for some releasees and crimino-suppressive effects for others, persists despite the inclusion of dozens covariates related to individual, peer, peer group, and contextual characteristics. However, in the narrower range where marginal prison peer effects appear significant (i.e., for the 20% or so of releasees who are most likely based on the observed information to cell with criminogenic cellmates), they appear criminogenic in both cases, even though the magnitudes of average prison peer effect estimates are negative and insignificant.

Switching effects. Where the treatment, $pricrime_c$ indicates whether a best cellmate had previously committed the crime under consideration and $rearrcrime_r$ indicates whether a releasee who had never previously committed that crime was rearrested for it in the four years post release, switching prison peer effects are estimated by estimating the following choice and outcome models for releasees who have not yet committed the crime type under consideration ($pricrime_r = 0$):

$$pricrime_c = \pi z + \gamma x_{rcptf} + \varepsilon_{rcptf}$$
$$rearrcrime_r = \alpha + \beta p + \delta x_{rcptf} + \varphi(p * x_{rcptf}) + u_{rcptf} \mid pricrime_r = 0$$

Again, marginal switching prison peer effects are calculated by differentiating the outcome with respect to the propensity score. Average switching prison peer effects are calculated by integrating over the marginal effects.

For switching effects, the difference of the Mills ratios suggests that unobserved heterogeneity remains a factor only for the releasees who have cellmates who have committed violent crimes: homicide and robbery (Reiss & Roth, 1993). For both crimes, the direction of the bias is the same: the positive and significant coefficient on k indicates that the unobserved characteristics of releasees who cell with violent criminals are negatively correlated with rearrest for a violent crime. First-time releasees who cell with murderers and robbers are less likely to commit those crimes than other members of the sample. (The inverse Mills ratio for the untreated releasees is negative, but insignificant.) As shown in Table 12, the tests for essential heterogeneity show that it (and, therefore, selection on gains) is present for each of the crime types, except contempt crimes. This is also evident in Figures 3 through 7.

Average prison peer effects fail to reach significance for the non-violent crimes, but are significant for robbery (p=0.015) and homicide (p=0.048). In both cases, the APPEs are negative. For releasees who had never committed robbery, the average effect is substantial, corresponding to a 16.59% decrease in the probability of being arrested for a robbery offense after celling with a robber (relative to not celling with a robber). For releasees who had never committed homicide, the effect is less substantial, corresponding to a 5.89% decrease in the probability of being arrested for a homicide after celling with a murderer (relative to not celling with a murderer).

Although the APPE for both violent crimes is negative, the downward-sloping MPPEs indicate that, for non-violent criminals, the probability of committing a violent crime is increasing in the observed propensity to cell with a violent criminal. Some MPPEs appear positive and significant, amounting to about a 10% increase in the probability of being arrested for homicide and about a 25% increase in the probability of being arrested for robbery at the extreme left end of the distribution of unobservables, U_D. This is the end of the distribution where unobservables play the least role in celling decisions, and where the observables play the most.

Reinforcing effects. The reinforcing effects models mirror the switching models, except for the baseline offending patterns of the releasees, which indicate experience with the crime type under consideration ($pricrime_r = 1$) like so:

$$pricrime_c = \pi z + \gamma x_{rcptf} + \varepsilon_{rcptf}$$
$$rearrcrime_r = \alpha + \beta p + \delta x_{rcptf} + \varphi\left(p * x_{rcptf}\right) + u_{rcptf} \mid pricrime_r = 1$$

Table 12 shows that essential heterogeneity appears to be a significant factor in reinforcing prison peer effects for each of the crimes types, except inchoate and weapons crimes. (The likelihood ratio test is significant at the 0.10 level for weapons violations, but does not approach significance for inchoate offenses.) However, little evidence of essential heterogeneity appears in Figures 9 through 14. The lines traced by the marginal prison peer effect estimates appear flat for all but drug crimes. Neither does unobserved heterogeneity appear to be a factor in the models. The coefficients on the inverse Mills ratios in both the treated and untreated groups are insignificant in each of the models and there are no significant differences between them, as indicated in Table 11.

Average prison peer effects are positive and significant for weapons offenses (p=0.014) and positive and marginally significant for motor vehicle theft (p=0.077). The estimates correspond to large increases in the probability of being arrested for weapons and motor vehicle theft crimes. First-time prison inmates who had previously stolen vehicles and then celled with a cellmate who had also previously stolen vehicles were 8.67% more likely to be rearrested for vehicle theft than similarly-situated first-timers who had not celled with a vehicle thief. Similarly, but more substantially, first-time releasees who had both committed weapons offenses and celled with a cellmate who also had weapons offenses in his background were 14.46% more likely to be rearrested for a weapons offense than similarly situated first-timers who were not celled with weapons offense violators.

Further Analysis: A Semiparametric Case

The preceding models have each been parametrically identified, but semi-parametric identification is also possible (Heckman et al., 2006; Brave & Walstrum, 2014). Semi-parametric identification relaxes the assumption of normality, so it depends crucially on the support of the propensity score (Apel & Sweeten, 2010; Brave & Walstrum, 2014). There must be both treated and untreated releasees to compare; otherwise the marginal prison peer effects cannot be computed. Graphs depicting the support of the propensity score appear in the upper panes of Figures 1 through 14.

A releasee's propensity score is the probability that he will be treated (i.e., celled with a cellmate with more criminal experience) based on the information observed about him in the data. In semiparametric estimation, the distribution of treated and untreated individuals along the zero to one range of the propensity score indicates whether average prison peer effects are appropriate summary statistics because it indicates where along the propensity score distribution there are both treated and untreated individuals to compare (Brave & Walstrum, 2014).

In the current sample, the propensity score can be said have *support* at points along the distribution of propensity scores where (nearly) the same propensity score is shared by both releasees whose best cellmate is more criminally experienced (i.e., are treated) and releasees whose best cellmate is less criminally experienced (i.e., are untreated). When the support of the propensity score is *full*, it has support for all values of the propensity score; and the treated and untreated groups are said to *balance* (Rosenbaum & Rubin, 1983, 1984; Heckman et al., 2006; Apel & Sweeten, 2010; Brave & Walstrum, 2014). That is, for each and every probability of being having a cellmate with more criminal experience, there are releasees who, in actually had cellmates with more criminal experience and releasees who had cellmates with less criminal experience. Marginal prison peer effects can be estimated wherever the propensity score has support. Average prison peer effects can only be estimated if the propensity score has full support.

Where APPEs cannot be calculated, local average prison peer effects can. To estimate the LAPPE parameter, MPPEs are integrated over a subset of the full zero to one range: u_D to $u_D{}'$:[13]

$$LAPPE(X) = \frac{1}{u_D - u_D{}'} \int_{u_D}^{u_D{}'} \Delta^{MPPE}(x, u_D) \partial u_D$$

Relative to the parametric estimates, the semiparametric APPE estimates show some attenuation for both switching and reinforcing effects, particularly where significant effects had been detected. These differences can be accounted for by examining the support of the propensity score.

The case of switching effects for homicide is instructive. As a reminder, the choice and outcome models estimated for switching effects look like:

$$prihomicide_c = \pi z + \gamma x_{rcptf} + \varepsilon_{rcptf}$$
$$rearrhomicide_r = \alpha + \beta p + \delta x_{rcptf} + \varphi\left(p * x_{rcptf}\right) + u_{rcptf} \mid prihomicide_r = 0$$

The output from those models appears in multiple formats. The upper pane of Figure 6 depicts the support of the propensity score for homicide switching effects; Table E2 in Appendix E presents both the parametric (P) and semiparametric (SP) prison peer effect estimates; and Figure F3 in Appendix F depicts both the parametric (upper pane) and semiparametric (lower pane) prison peer effect estimates. Table E2 reveals that the APPE for homicide remained significant, but nearly tripled in magnitude, from -0.0589 to -0.1692, in the semiparametric specification. Consider, however, Figure 6, which shows that the support of the propensity score for homicide is not full: only standardized values for the unobservables that lie between about zero and 0.5 are supported.

[13] There are many other treatment effect parameters. All are weighted versions of the marginal treatment effect parameter. Heckman and Vytlacil (2005) detail the appropriate weighting strategies for each of the other treatment effect parameters, a discussion that is beyond the scope of the current study (pp. 680-681).

Integrating over the MPPEs for homicide switching effects between those values yields an LAPPE of -0.4295,[14] thus indicating that the APPEs are somewhat misleading, regardless of whether they are estimated parametrically or semiparametrically.

To be clear, the support of the propensity score indicates for whom the prison peer effect estimates are reliable. They are reliable where the propensity score is supported. In the case of switching effects for homicide, the propensity score is supported in the range from near zero to about a 50% probability of celling with a murderer. Additionally, while releasees who experienced significantly positive effects are far fewer than those who experienced significantly negative effects, the range of the MPPEs is still substantial. Examining only the region where the error bands around the marginal prison peer effects indicate significance, the spread is nearly ten percentage points: at its peak near $U_D = 0.10$, the estimated MPPE is positive 0.0149, while at $U_D = 0.30$, it is negative: -0.0803.

DISCUSSION

By exploring the potential for heterogeneity in cellmate social interaction effects, this study has provided the first causal prison peer estimates for a sample of adult releasees from a U.S. state prison system. Like many peer effect studies, the current study has produced little evidence of average peer effects on general offending behavior. Unlike those studies, the current study has shown that essential heterogeneity plays a role in producing those outcomes. Marginal prison peer effects vary. Upon exploring one potential source of that heterogeneity, variation in the types of crimes committed, significant switching and reinforcing effects emerged. As expected, some of those are criminogenic and some are crimino-suppressive, which helps to explain the average null effects.

Summary of Results

This collection of results is instructive in terms of the variability of the prison peer effect estimates. APPE estimates for the prevalence of reincarceration and rearrest point in the crimino-suppressive direction, but are statistically insignificant, with MPPE estimates for both outcomes pointing in both the criminogenic and crimino-suppressive directions: some releasees were likely harmed (i.e., encouraged to persist in criminal behavior), while other releasees were likely helped (i.e., encouraged to desist from criminal behavior) by associating with their longest-duration, best cellmates.

Variation in MPPE estimates indicates the presence of essential heterogeneity in the relationship between a releasee's probability of reoffending and the criminal experience of his

[14] The LAPPE were calculated from the semiparametrically estimated MPPEs, as they are not reported from *margte*.

cellmate. Specifically, the MPPEs decrease as the unobserved determinants of celling with a cellmate with a prior incarceration become more important, which implies an increasing probability of being rearrested or reincarcerated as a releasee's observed propensity to cell with a formerly incarcerated cellmate increases. Additionally, although the average prison peer effect estimates are negative but insignificant, the marginal prison peer effects are significant for about 20% of the releasees. Where the MPPE estimates are significant, they are criminogenic and similar in magnitude for both outcomes, corresponding to about a 20% local average increase in the probability of being rearrested or reincarcerated after interacting with a more criminally experienced cellmate. Even within this local average, the MPPE estimates vary substantially between about an 8% and about a 35% increase in the probability of reoffending after celling with a previously incarcerated cellmate.

The rearrest and reincarceration models include scores of covariates to account for releasee, cellmate, social group (i.e., cellmate pool), facility, and other contextual and timing characteristics. Yet the marginal prison peer effect estimates vary because some determinants of the types of cellmates with whom releasees choose to spend long periods of time remain unknown. Variables are omitted. Specifically, the model specifications for rearrest and reincarceration omit information on the types of crimes committed by the releasees or their cellmates.

Variation in prison peer effects by crime type appears to be one source of the essential heterogeneity observed in the rearrest and reincarceration outcomes. Some crime types exhibit no significant average prison peer effects, some exhibit significantly positive prison peer effects, and some exhibit significantly negative prison peer effects. This finding lends support to the criminological literature that favors etiological differences in offending behaviors because cellmate criminal experience appeared to differentially affect releasee offending behaviors (Sutherland, 1947).

Switching and reinforcing marginal prison peer effect estimates also varied for some crime types, thereby indicating the presence of essential heterogeneity. As was the case with the reincarceration and rearrest MPPEs, decreases in the MPPEs with respect to the unobservables are evidenced for homicide and robbery switching effects, similarly indicating increasing returns (higher probability of rearrest for homicide and robbery) for releasees who had not committed homicide or robbery as they exhibit higher propensities to cell with cellmates who had committed those crimes. However, although the MPPEs show increasing returns, they show increasing returns across negative effects. The APPEs for both violent crimes are negative, indicating generally crimino-suppressive effects.

While the prison peer effects estimated for drug crimes are not significant at the 0.05 level in any of the parametric models,[15] it is instructive to consider them in contrast to the previously discussed results for violent crimes because the opposite in terms of MPPEs appears to be true for them. For both switching and reinforcing effects APPE for drug crimes appear criminogenic, but Figures 5 and 12 suggest that MPPEs for drug crimes exhibit an increasing relationship to the unobserved determinants of celling with a drug-involved cellmate. Therefore, as releasees become more likely, based on their propensity scores, to cell with drug-involved cellmates, they appear to become less likely to be rearrested for drug offenses.

The other crime types studied exhibit no essential heterogeneity. Figures 11, 13, and 14, which depict marginal and average prison peer effect estimates at mean covariate values for reinforcing effects on assault, motor vehicle theft, and weapons, respectively, show this best. The plot of the marginal prison peer effects (solid line) is flat or very nearly flat for all three. Assault offenses exhibit null APPEs, whereas motor vehicle theft and weapons offenses exhibit positive and significant APPEs, which equate to MPPEs due to the lack of essential heterogeneity.

In addition to lacking essential heterogeneity, the reinforcing prison peer effect for weapons crimes is large, criminogenic, and consistent in both parametric and semiparametric estimation. Releasees who have weapons violations in their background who cell other inmates who also have weapons violations in their background are about 15% more likely to be rearrested for a weapons violation, relative to similarly situated releasees whose cellmates lack prior weapons violations.

Oh the whole, prison peer influence appears most relevant to violent offending, but effects vary. Reinforcing effects for weapons violations are universally criminogenic, whereas average switching effects for violent crimes (robbery and homicide) are crimino-suppressive, but are also inclusive of marginal effects that are criminogenic as well as crimino-suppressive. While weapons offense are more prevalent post-release (n=948), robbery (n=433) and homicide (n=179) are potentially more serious crimes; and occurred with nontrivial frequency. These crimes may also be comorbid: 57.27% of the reoffending robbers also have weapons offenses, as do 72.07% of the reoffending murderers. Even 27.93% of the murderers also have robbery charges. Thus, another form of heterogeneity is suggested: degree of specialization (e.g., Farrington, Snyder, & Finnegan, 1988).

[15] They are significant at the 0.10 level in the semiparametric models.

Limitations

This study has many limitations. It examines prison peer effects only for first-time releasees, who are assumed to be single decision-makers, even though decision makers may be many. It examines the effect of only one cellmate on those releasees, even though many cellmates may affect them. In examining the effect of that single cellmate, only one dimension of that cellmate is considered, even though people are multi-dimensional. Although many outcomes are considered, each is a blunt and potentially weak, dichotomous indicator of reoffending behavior (Sweeten, 2012). Still, this study attempts what no study to date has attempted: to isolate causal prison peer effects under essential heterogeneity in a sample of formerly-incarcerated adults.

First-time releasees were chosen because they were expected to experience the most extreme prison peer effects (Wheeler, 1961; Nieuwbeerta et al., 2009). First-timers also constitute the majority of releasees from PADOC. In 2006 and 2007, 17,582 unique prisoners were released from PADOC custody. Of those, 12,494 (71.06%) were first-timers. Still, the findings reported by the current study are generalizable only to first-time prison inmates. Expanding the sample to include all releasees would allow for (rare) comparisons between the impact of prison peers on the reoffending outcomes of first-time and returning prisoners.

Longest-duration cellmates were chosen because they were expected to exert the most extreme prison peer effects (Sutherland, 1947; Agnew, 1991; Warr, 1993; Haynie et al., 2005), but cellmates other than the longest-duration cellmates could be more relevant to releasee reoffending. Clemmer (1940) ascribed importance to first cellmates because inmates "seem to rely greatly on [their] first impressions of people" and the "first contacts" that they make in prison (p. 100). Last cellmates might also be especially relevant because the peak-end rule suggests that the most intense and the most recent experiences are the most salient (Kahneman et al. 1997). Other cellmate associations can be explored in future work, although as shown in Appendix D, even most characteristics of the best cellmates did not independently affect releasee reoffending, a finding that may cast some doubt on prior prison peer evidence based on facility-level effects aggregated from individual offending histories (e.g., Bayer et al., 2009).

In the prison peer context (and in the context of social interaction effects more generally), the treatment decision is less well-defined than it is in other contexts. In standard Roy (1951) models, the decision to, for example, complete high school or not is a well-structured binary choice (e.g., Heckman et al., 2006; Heckman & Urzúa, 2010). Here, treatment reflects the criminal experience of best cellmates, in interaction with releasee characteristics. While well-defined in terms of delineating more or less criminality and well-supported theoretically, the treatments are not well-encapsulated into homogenous treatments because people are not uni-dimensional. Other means of capturing variation in criminal experience, such as exploring variation in modes of committing crime, which may be available in inmates' narrative accounts of their crimes, may prove fruitful.

The dichotomous outcome measures are blunt measures of reoffending, both conceptually and operationally. Conceptually, rearrest and reincarceration are official measures that reflect both individual and institutional action. The individual and institutional elements of the reoffending measures cannot be separated (Maltz, 1984). As such, the reoffending measures may poorly reflect actual offending behavior, which may limit their utility as indicators of prison peer influence. Operationally, while dichotomous measures are the most frequently used measures in the criminological literature, Sweeten (2012) argued that they are the "simplest and weakest" (p. 542) because they ignore "all seriousness and frequency of offending" (p. 552). In the current study, seriousness is accounted for by the crime type interactions, while frequency outcomes are not realistic. Most of the PADOC releasees who were rearrested (n=5,214), were only arrested once (n=2,755) and only 11% were arrested more than three times.

Sweeten (2012) noted that dichotomous measures "should only be used if they are shown to be robust to known methodological shortcomings" (p. 554), a valid objection their use in the context of LIV, which expects continuous outcomes. However, the application of continuous models to dichotomous outcomes is common in the treatment effect literature (Brock & Durlauf, 2001, 2007; Angrist & Pischke, 2009; Chesher & Rosen, 2013). Furthermore, Angrist and Pischke (2009) argue that the dichotomous nature of the outcome variable is inconsequential when estimating marginal effects because the area over which the estimation occurs is so minute. Nevertheless, an extension of the LIV framework to dichotomous outcomes or the exploration of continuous outcomes would improve the internal validity of the estimation process.

Finally, to avoid SUTVA violations, the agency of the releasee was adopted as the ultimate driver of the decision to cell with a more criminally experienced cellmate. While this perspective can be justified, it fails to accurately characterize the celling decision, which also involves the agency of cellmates and correctional personnel. Adopting this perspective also renders interpretation of the unobservables untenable: too many factors are potentially unobservable. However, all regression-based models of peer influence make the same assumptions and are subject to the same limitations, but without the added benefit of being able to characterize the collective contribution of the observables (Wellford, 1973; Manski, 1993; Mouw, 2006; Gangl, 2010; Durlauf & Ioannides, 2010;

Graham, 2011; Sacerdote, 2014). Were the LIV model extended to accommodate multiple decision makers, it might be possible to separate the unobservables into unobservables attributable to each decision maker. Doing this would highlight decision spaces where future research could concentrate to better understand individual outcomes.

Future Directions and Wider Applicability

The primary goal of the current study has been to determine whether cellmates matter in the production of reoffending. The answer is clear: cellmates matter. But they do not matter the same for everyone. At the margin of the probability of remaining with a cellmate some inmates are affected positively by their cellmate associations in that they are more likely to desist from crime and some are affected negatively in that they are more likely to persist in crime. The effects are strongest for violent crimes, but point in opposite directions, with criminogenic effects for weapons offenses and mostly crimino-suppressive effects for homicide and robbery.

While parametric assumptions allowed for identification of average prison peer effects for overall and crime-specific reoffending, the support of the propensity scores suggests caution in their interpretation. As the semiparametric analyses showed, there are not always comparisons to be made along the propensity score range. Biased samples yield biased results (Brave & Walstrum, 2014; Basu et al., 2007). Moreover, even when estimated APPEs (or even LAPPEs) were significant and supported, the MPPEs were rarely heterogeneity-free and often pointed in opposite directions. This is problematic for policy. To avoid doing harm to some, while also helping some, we must begin to better understand to whom "average" effects really apply (Sherman, 2007).

While affirmative of the potential for peer influence to affect offending behavior among adults, and while informative with respect to the genesis of null average peer and prison effects, these results are somewhat dissatisfying because the questions that naturally emerge as a result of them go unanswered: What are the remaining unobserved factors that determine cellmate associations? Even though response heterogeneity persists, can we use these results to better determine which releasees are most likely to desist from and which releasees are most likely to persist in criminal offending after associating with particular types of cellmates? Can we say anything about why?

The answer is: not without further analysis. Heckman and Vytlacil (1999) and Basu (2014) show that answering the aforementioned questions may be possible, in particular by estimating person-centered treatment effects. The local instrumental variables framework, therefore, offers a means through which the potential to reduce, or at least not exacerbate, reoffending through cellmate assignments may become possible. If definitive trends emerge within the observable information to suggest that some prisoners routinely reoffend after particular cellmate pairings, whereas other prisoners do not, it may become possible to avoid the pairings that lead to persistence and to encourage the ones that lead to desistance.

On that point, caution should be exercised. Sacerdote (2014, p. 1) warned against the temptation to recommend policies to reallocate peers to manipulate peer effects. "[D]espite potential temptation," he wrote, "we have not reached the point at which we can reliably use knowledge of peer effects to implement policies that improve outcomes for students and other human subjects" (e.g., Carrell, Sacerdote, & West, 2013). That is certainly true in the nascent study of prison peer effects. Therefore, a central task for future prison peer research will be to gather more knowledge regarding the unobserved determinants of cellmate associations (e.g., inmate and institutional preferences) and to apply that knowledge to predict the effects of potential associations, just as researchers are now attempting to prospectively predict the effects of potential sentencing policy shifts (Reitz, 2009) and medical treatments (Basu, 2014).

Despite its inability to characterize those who persist and those who desist after cellmate associations, the current analysis helps to explain two findings in two literatures. One, from the peer effect literature, indicates that there is limited and heavily context-dependent evidence of peer effects (Hartup, 2005; Mouw, 2006; Gangl, 2010; Horney et al., 2012; Angrist, 2013; Sacerdote, 2014). The other, from the prison effect literature, says that prison effects, whether measured by time served or the in/out decision, appear null or mildly criminogenic (Nagin et al., 2009; Loughran et al., 2009; Green & Winik, 2010; Snodgrass et al., 2011; Loeffler, 2013; Nagin & Snodgrass, 2013; Meade et al., 2013). The story is the same for both: characterizing broad samples in terms of average effects on generic outcomes is unlikely to yield much in the way of social interaction or prison effects. Those who experience positive and those who experience negative marginal (prison or social interaction) effects cancel each other out.

CONCLUSION

This study has been an initial examination of prison peer effects in U.S. adult sample. Like other peer effect studies, it showed little in the way of causal average prison peer effects. However, after looking a little deeper, a source of the variation in those null averages was revealed: variation in types of criminal offending. Some prison inmates are significantly harmed via their cellmate interactions in that they persist in crime, while cellmate interactions help others significantly, in that they desist from crime. The effects, both positive and negative, appear most profound for violent crimes, including homicide, robbery, and weapons offenses. For weapons offenses, the effects were solidly and consistently criminogenic, revealing little essential heterogeneity. For homicide and robbery, average prison peer effect estimates were crimino-suppressive, but included significantly criminogenic marginal prison peer effects due to essential heterogeneity. The next steps will be to better determine who cellmate associations harm, who they help, and why.

TABLES

Table 1: Descriptive Statistics

	Releasees		Best Cellie		Cellie Pool	
Demographics	Mean	SD	Mean	SD	Mean	SD
Age	30.26	9.8	31.56	9.9	31.76	5.6
Single	76.55%		72.95%		74.40%	22.7%
Black	41.83%		44.98%		44.72%	35.4%
Latino	13.46%		12.97%		13.23%	21.4%
From an Urban County	75.55%		78.87%		78.53%	22.4%
High School or GED	59.83%		60.10%		59.31%	24.6%
Reports Prior Employment	24.73%		34.81%		35.30%	24.2%
US Veteran	5.89%		6.71%		6.60%	12.6%
IQ	91.28	13.6	91.46	13.6	91.10	7.1
Reports Medical Limits	19.15%		21.68%		22.02%	20.4%
Reports Sexual Problems	12.67%		19.83%		18.36%	20.0%
Reports MH Problems	33.58%		32.85%		35.47%	25.1%
Reports SA Problems	93.13%		91.33%		91.58%	13.8%
Time Served	845.65	562.3	NA		NA	
Has an Escape History	49.07%		50.59%		51.57%	24.8%
Has an A/B Misconduct	24.52%		41.78%		35.81%	26.1%
Has TC	17.51%		20.69%		20.84%	21.7%
Has Custody Level > 3	23.75%		23.95%		29.34%	25.4%
Maximum Sentence	64.02	39.3	191.04	384.4	151.74	148.0
Time Served	845.65	562.3	NA		NA	
Criminal History	Mean	SD	Mean	SD	Mean	SD
No. Prior Arrests	5.55	4.3	6.48	5.6	6.82	2.9
Has Prior Incarceration	29.76%		22.81%		30.20%	22.8%
Is A Lifer	NA		4.01%		2.55%	7.3%
18 or Under at First Arrest	34.82%		34.66%		36.85%	25.4%
Cellmate Info	Mean	SD	Mean	SD	Mean	SD
Time Served at Pairing	NA		27.24	46.2	NA	
Time to Release at Pairing	529.38	427.9	NA		NA	
Total Cellie Pool Time	NA		NA		380.96	354.3
Pct. Stay with Cellmate	24.79	15	NA		NA	
Stretches with Cellmate	1.57	1.1	NA		NA	
No. Cellies	14.01	9.3	NA		NA	
Contextual Covariates	Mean	SD	Mean	SD	Mean	SD
Cell on Upper Tier	50.37%		NA		NA	
Cellie Into Releasee's Cell	33.30%		NA		NA	
Releasee Into Cellie's Cell	43.25%		NA		NA	
Release Timing	Mean	SD	Mean	SD	Mean	SD
Releasee Time to Release	529.38	427.9	NA		NA	
Release in 2Q 2006	12.53%		NA		NA	
Release in 3Q 2006	11.47%		NA		NA	
Release in 4Q 2006	11.52%		NA		NA	
Release in 1Q 2007	12.50%		NA		NA	
Release in 2Q 2007	12.89%		NA		NA	
Release in 3Q 2007	13.36%		NA		NA	

Release in 4Q 2007	13.68%		NA		NA	
Outcomes	Mean	SD	Mean	SD	Mean	SD
Has Post Incarceration	46.30%		NA		NA	
Has Post Arrest	51.54%		NA		NA	
No. Post Arrests	0.99	1.4	NA		NA	
Instruments	Mean	SD	Mean	SD	Mean	SD
Bed Availability on Unit	3.41	3.3	NA		NA	
First Cell Sq. Footage	82.95	12.8	NA		NA	
Same Race	77.54%		NA		NA	
Same Commit County	19.54%		NA		NA	

Table 2: Crime Type Categories and Offending Prevalences

Prevalence of Prior and Post Arrest by Crime Type, n=10,116 Releasee (R) - Cellmate (C) pairs							
Type P Crimes	R Pri=1	C Pri=1	R Post=1	Type Q Crimes	R Pri=1	C Pri=1	R Post=1
Public Admin	4,028	4,179	1,592	Abortion	8	5	7
Drugs	6,701	6,072	2,523	Aiding or Soliciting	30	44	2
Family	384	577	89	Liquor Law	35	43	1
Inchoate	4,799	5,827	988	Animal Control	15	63	1
Public Order	5,683	5,568	2,055	Animal Cruelty	45	57	6
Person	6,474	7,747	1,914	Assault	5,561	6,563	1,620
Property	7,229	7,616	2,108	Burglary	2,741	3,392	544
Unknown	2,942	2,187	30	Child Sex Assault	427	641	58
				Conduct	3,702	3,527	1,116
				Conspiracy	2,689	3,548	36
				Contempt	2,806	2,886	895
				Corruption of Minors	1,073	1,319	114
				Corruption	85	111	13
				DUI	2,211	1,897	849
				Property Damage	2,830	3,006	514
				Delinquency	555	505	4
				Drugs	6,707	6,084	2,526
				Escape	817	933	255
				Fraud	2,297	2,163	798
				Habitual Offending	26	22	36
				Harassment	3,490	4,091	991
				Homicide	887	1,880	179
				Kidnapping	634	1,158	173
				Motor Vehicle Theft	1,799	2,072	219
				Neglect (Dependent)	418	563	147
				Property Maintenance	17	118	3
				Parking Violation	2	13	0
				Pornography	39	58	8
				Prostitution	56	68	22
				Rape	479	1,063	51
				Fail to Register	20	38	70
				Robbery	2,565	3,611	435
				Sex Assault	1,007	1,619	128
				Statutory Rape	370	578	25
				Terrorism	10	8	4
				Theft	6,293	6,699	1,602
				Trespassing	3,020	3,332	799
				Unknown	2,701	2,371	314
				Motor Vehicle	68	66	16
				Weapons	3,593	4,592	953

Table 3: Linear probability model for releasee reincarceration and rearrest as a function of cellmate prior incarceration

Rearrest

var	coef	stderr	pval	N	r2	file
c_hasPriorI	.0321863	.0108639	.0030568	10116	.0008671	1
c_hasPriorI	.032025	.0108439	.0031514	10116	.016306	2
c_hasPriorI	.0237521	.0098498	.0159078	10116	.1960861	3
c_hasPriorI	.0316931	.0114124	.005495	10116	.1991219	4
c_hasPriorI	.0326222	.0114258	.0043107	10116	.2016561	5
c_hasPriorI	.0324573	.0114559	.0046171	10116	.2031731	6
c_hasPriorI	.0304583	.0115096	.0081497	10116	.2054339	7

Reincarceration

var	coef	stderr	pval	N	r2	file
c_hasPriorI	.013155	.0108432	.2250793	10116	.0001455	1
c_hasPriorI	.0131207	.0108889	.2282473	10116	.0036128	2
c_hasPriorI	.0127255	.0100451	.2052428	10116	.1600943	3
c_hasPriorI	.0195316	.0116242	.0929412	10116	.1653333	4
c_hasPriorI	.0198046	.011615	.0882092	10116	.1712517	5
c_hasPriorI	.0198907	.0116408	.0875369	10116	.1735116	6
c_hasPriorI	.0183993	.0116853	.1153896	10116	.1772646	7

Table 4: Two-stage least-squares estimates and instrument tests for releasee reincarceration and rearrest as a function of cellmate prior incarceration

outcome	var	coef	stderr	pval	N	r2
rearr	c_hasPriorI	-.1691822	.1464053	.2478554	10116	.1811034
reinc	c_hasPriorI	-.2683333	.1526783	.0788314	10116	.127263

Rearrest IV tests

```
------------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):              60.713
                                                   Chi-sq(4) P-val =    0.0000
------------------------------------------------------------------------------
Weak identification test (Kleibergen-Paap rk Wald F statistic):          14.530
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias    16.85
                                         10% maximal IV relative bias    10.27
                                         20% maximal IV relative bias     6.71
                                         30% maximal IV relative bias     5.34
                                         10% maximal IV size             24.58
                                         15% maximal IV size             13.96
                                         20% maximal IV size             10.26
                                         25% maximal IV size              8.31
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):          5.683
                                                   Chi-sq(3) P-val =    0.1281
------------------------------------------------------------------------------
```

Reincarceration IV tests

```
------------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):              60.713
                                                   Chi-sq(4) P-val =    0.0000
------------------------------------------------------------------------------
Weak identification test (Kleibergen-Paap rk Wald F statistic):          14.530
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias    16.85
                                         10% maximal IV relative bias    10.27
                                         20% maximal IV relative bias     6.71
                                         30% maximal IV relative bias     5.34
                                         10% maximal IV size             24.58
                                         15% maximal IV size             13.96
                                         20% maximal IV size             10.26
                                         25% maximal IV size              8.31
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):          5.923
                                                   Chi-sq(3) P-val =    0.1154
------------------------------------------------------------------------------
```

Table 5: Linear probability models for switching effects

var	coef	stderr	pval	N	r2	file	
c_pri_p1	.0158385	.0084735	.0616463	6088	.0005737	p1	[Public Admin]
c_pri_p2	.0311597	.0104756	.002955	3415	.0025857	p2	[Drugs]
c_pri_p4	.0126692	.0057308	.027097	5317	.0009187	p4	[Inchoate]
c_pri_p5	.0031125	.0109059	.7753505	4433	.0000184	p5	
c_pri_p6	.0150974	.0124149	.2240381	3642	.0004061	p6	
c_pri_p7	.0078711	.0111919	.4819384	2887	.0001714	p7	

var	coef	stderr	pval	N	r2	file	
c_pri_h11	.0139738	.0066216	.0348622	7310	.000609	h11	[Contempt]
c_pri_h12	-.0016765	.0031709	.5970198	9043	.0000309	h12	
c_pri_h14	-.0011684	.0074897	.8760355	7905	3.08e-06	h14	
c_pri_h15	.005809	.0046894	.2154814	7286	.0002106	h15	
c_pri_h17	.0297766	.010482	.0045279	3409	.002363	h17	[Drugs]
c_pri_h18	.0004534	.0053433	.9323742	9299	7.75e-07	h18	
c_pri_h19	.0084629	.0066493	.2031439	7819	.0002072	h19	
c_pri_h21	.0053867	.0065886	.4136276	6626	.0001009	h21	
c_pri_h22	.0086081	.0033439	.0100614	9229	.0007177	h22	[Homicide]
c_pri_h23	.0044502	.00404	.270698	9482	.000128	h23	
c_pri_h24	.0045059	.0031773	.1561781	8317	.0002418	h24	
c_pri_h25	-.006553	.0052385	.2109899	9698	.0001614	h25	
c_pri_h32	.0161015	.0040638	.0000749	7551	.0020753	h32	[Robbery]
c_pri_h33	.0012988	.0029017	.6544441	9109	.000022	h33	
c_pri_h36	-.0018099	.0079485	.8198853	3823	.0000136	h36	
c_pri_h37	.004564	.0062693	.4666364	7096	.0000747	h37	
c_pri_h40	.0174561	.005451	.0013695	6523	.0015702	h40	[Weapons]
c_pri_h6	.0125026	.0092578	.1769235	4555	.0004004	h6	
c_pri_h7	.0026346	.0045447	.5621226	7375	.0000456	h7	
c_pri_h9	.0103765	.0070534	.1413039	6414	.0003374	h9	

Table 6: Two-stage least squares estimates and instrument tests for switching effects

var	coef	stderr	pval	N	r2	
c_pri_p2	.1218125	.1123241	.2781551	3415	.0815278	Drugs (P)
c_pri_h11	-.0424374	.1789013	.812493	7310	.0469599	Contempt
c_pri_h17	.1011062	.1130283	.3710431	3409	.0906549	Drugs (Q)
c_pri_h22	-.0544923	.0411347	.1852614	9229	.010646	Homicide
c_pri_h32	-.003944	.0829902	.9620959	7551	.0469333	Robbery

Drug IV tests (Type P)

```
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):           40.150
                                                   Chi-sq(3) P-val =    0.0000
------------------------------------------------------------------------------
Weak identification test (Kleibergen-Paap rk Wald F statistic):       15.253
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias    13.91
                                         10% maximal IV relative bias     9.08
                                         20% maximal IV relative bias     6.46
                                         30% maximal IV relative bias     5.39
                                         10% maximal IV size             22.30
                                         15% maximal IV size             12.83
                                         20% maximal IV size              9.54
                                         25% maximal IV size              7.80
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):        0.652
                                                   Chi-sq(2) P-val =     0.7219
--------------------------------------------------------------------------
```

Contempt IV tests

```
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):           13.525
                                                   Chi-sq(2) P-val =    0.0012
------------------------------------------------------------------------------
Weak identification test (Kleibergen-Paap rk Wald F statistic):        6.685
Stock-Yogo weak ID test critical values: 10% maximal IV size             19.93
                                         15% maximal IV size             11.59
                                         20% maximal IV size              8.75
                                         25% maximal IV size              7.25
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):        1.699
                                                   Chi-sq(1) P-val =    0.1924
------------------------------------------------------------------------------
```

Drug IV tests (Type Q)

```
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):           39.586
                                                   Chi-sq(3) P-val =    0.0000
------------------------------------------------------------------------------
Weak identification test (Kleibergen-Paap rk Wald F statistic):       15.046
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias    13.91
                                         10% maximal IV relative bias     9.08
                                         20% maximal IV relative bias     6.46
                                         30% maximal IV relative bias     5.39
                                         10% maximal IV size             22.30
                                         15% maximal IV size             12.83
                                         20% maximal IV size              9.54
                                         25% maximal IV size              7.80
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):        0.693
                                                   Chi-sq(2) P-val =    0.7071
------------------------------------------------------------------------------
```

Homicide IV tests

```
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):            44.079
                                                   Chi-sq(2) P-val =    0.0000
------------------------------------------------------------------------------
Weak identification test (Kleibergen-Paap rk Wald F statistic):        23.003
Stock-Yogo weak ID test critical values: 10% maximal IV size            19.93
                                         15% maximal IV size            11.59
                                         20% maximal IV size             8.75
                                         25% maximal IV size             7.25
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):        0.565
                                                   Chi-sq(1) P-val =    0.4522
------------------------------------------------------------------------------
```

Robbery IV tests

```
------------------------------------------------------------------------------
Weak identification test (Kleibergen-Paap rk Wald F statistic):         7.857
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias   13.91
                                         10% maximal IV relative bias    9.08
                                         20% maximal IV relative bias    6.46
                                         30% maximal IV relative bias    5.39
                                         10% maximal IV size            22.30
                                         15% maximal IV size            12.83
                                         20% maximal IV size             9.54
                                         25% maximal IV size             7.80
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):        2.423
                                                   Chi-sq(2) P-val =    0.2977
------------------------------------------------------------------------------
```

Table 7: Linear probability models for reinforcing effects

var	coef	stderr	pval	N	r2	file	
c_pri_p1	.0241726	.0130454	.0639611	4028	.0008521	p1	[Public Admin]
c_pri_p2	.0607101	.011923	3.64e-07	6701	.0038554	p2	[Drugs]
c_pri_p4	.039945	.0108403	.0002314	4799	.0028226	p4	[Inchoate]
c_pri_p5	.0022862	.0115304	.8428367	5683	6.92e-06	p5	
c_pri_p6	.0366478	.0126437	.003762	6474	.0012964	p6	[Person]
c_pri_p7	.027954	.0122469	.0224865	7229	.0007204	p7	[Property]

var	coef	stderr	pval	N	r2	file	
c_pri_h11	.0092091	.0141446	.5150532	2806	.0001512	h11	
c_pri_h12	.003689	.0112498	.743037	1073	.0001004	h12	
c_pri_h14	-.004757	.0171389	.7813796	2211	.0000349	h14	
c_pri_h15	-.0067456	.0117744	.5667552	2830	.000116	h15	
c_pri_h17	.0594526	.0119263	6.35e-07	6707	.0036925	h17	[Drugs]
c_pri_h18	.0049861	.0256959	.8461896	817	.0000462	h18	
c_pri_h19	.0180243	.0171411	.2931281	2297	.0004816	h19	
c_pri_h21	.0113287	.0119502	.3431976	3490	.0002576	h21	
c_pri_h22	.0065983	.0156033	.6724896	887	.000202	h22	
c_pri_h23	.0872141	.0210268	.0000382	634	.0265	h23	[Kidnapping]
c_pri_h24	.0250924	.012733	.0489164	1799	.0021564	h24	[MVT]
c_pri_h25	.0263158	.0284497	.355505	418	.0020525	h25	
c_pri_h32	.0050248	.0111139	.6512236	2565	.0000797	h32	
c_pri_h33	.0213188	.0135376	.1156225	1007	.0024615	h33	
c_pri_h36	-.0043205	.0112094	.6999259	6293	.0000236	h36	
c_pri_h37	.0002281	.0119955	.9848275	3020	1.20e-07	h37	
c_pri_h40	.0513275	.012706	.0000547	3593	.0045238	h40	[Weapons]
c_pri_h6	.0562695	.0115768	1.20e-06	5561	.0042318	h6	[Assault]
c_pri_h7	.0016285	.0121742	.8935975	2741	6.53e-06	h7	
c_pri_h9	.005497	.0126404	.6636784	3702	.0000511	h9	

Table 8: Two stage least squares for reinforcing effects

var	coef	stderr	pval	N	r2	
c_pri_p2	-.1145386	.1129821	.3106894	6701	.1339681	Drugs (P)
c_pri_p4	.137953	.137188	.3146197	4799	.0866739	Inchoate
c_pri_h6	.6580402	.3282174	.0449746	5561	-.3553597	Assault
c_pri_h17	-.1106471	.1130885	.3278711	6707	.134841	Drugs (Q)
c_pri_h24	.2558745	.1643108	.1194091	1799	-.053488	MVT
c_pri_h40	.1616146	.0927286	.0813551	3593	.0924787	Weapons

Drugs (Type P) IV tests

```
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):             71.632
                                                   Chi-sq(3) P-val =    0.0000
------------------------------------------------------------------------------
Weak identification test (Kleibergen-Paap rk Wald F statistic):         26.798
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias    13.91
                                         10% maximal IV relative bias     9.08
                                         20% maximal IV relative bias     6.46
                                         30% maximal IV relative bias     5.39
                                         10% maximal IV size             22.30
                                         15% maximal IV size             12.83
                                         20% maximal IV size              9.54
                                         25% maximal IV size              7.80
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):         2.139
                                                   Chi-sq(2) P-val =    0.3432
------------------------------------------------------------------------------
```

Inchoate IV tests

```
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):             27.015
                                                   Chi-sq(3) P-val =    0.0000
------------------------------------------------------------------------------
Weak identification test (Kleibergen-Paap rk Wald F statistic):          9.049
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias    13.91
                                         10% maximal IV relative bias     9.08
                                         20% maximal IV relative bias     6.46
                                         30% maximal IV relative bias     5.39
                                         10% maximal IV size             22.30
                                         15% maximal IV size             12.83
                                         20% maximal IV size              9.54
                                         25% maximal IV size              7.80
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):         2.791
                                                   Chi-sq(2) P-val =    0.2476
------------------------------------------------------------------------------
```

Assault IV tests

```
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):             12.948
                                                   Chi-sq(2) P-val =    0.0015
------------------------------------------------------------------------------
Weak identification test (Kleibergen-Paap rk Wald F statistic):          6.405
Stock-Yogo weak ID test critical values: 10% maximal IV size             19.93
                                         15% maximal IV size             11.59
                                         20% maximal IV size              8.75
                                         25% maximal IV size              7.25
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):         0.119
                                                   Chi-sq(1) P-val =    0.7303
------------------------------------------------------------------------------
```

Drugs (Type Q) IV tests

```
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):             71.541
                                                  Chi-sq(3) P-val =    0.0000
------------------------------------------------------------------------------
Weak identification test (Kleibergen-Paap rk Wald F statistic):         26.773
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias    13.91
                                         10% maximal IV relative bias     9.08
                                         20% maximal IV relative bias     6.46
                                         30% maximal IV relative bias     5.39
                                         10% maximal IV size             22.30
                                         15% maximal IV size             12.83
                                         20% maximal IV size              9.54
                                         25% maximal IV size              7.80
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):         2.197
                                                  Chi-sq(2) P-val =    0.3334
------------------------------------------------------------------------------
```

Motor Vehicle Theft IV tests

```
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):             14.393
                                                  Chi-sq(2) P-val =    0.0007
------------------------------------------------------------------------------
Weak identification test (Kleibergen-Paap rk Wald F statistic):          6.833
Stock-Yogo weak ID test critical values: 10% maximal IV size             19.93
                                         15% maximal IV size             11.59
                                         20% maximal IV size              8.75
                                         25% maximal IV size              7.25
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):         0.031
                                                  Chi-sq(1) P-val =    0.8603
------------------------------------------------------------------------------
```

Weapons IV tests

```
------------------------------------------------------------------------------
Underidentification test (Kleibergen-Paap rk LM statistic):             83.110
                                                  Chi-sq(4) P-val =    0.0000
------------------------------------------------------------------------------
Weak identification test (Kleibergen-Paap rk Wald F statistic):         21.482
Stock-Yogo weak ID test critical values:  5% maximal IV relative bias    16.85
                                         10% maximal IV relative bias    10.27
                                         20% maximal IV relative bias     6.71
                                         30% maximal IV relative bias     5.34
                                         10% maximal IV size             24.58
                                         15% maximal IV size             13.96
                                         20% maximal IV size             10.26
                                         25% maximal IV size              8.31
Source: Stock-Yogo (2005).  Reproduced by permission.
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.
------------------------------------------------------------------------------
Hansen J statistic (overidentification test of all instruments):         0.867
                                                  Chi-sq(3) P-val =    0.8335
------------------------------------------------------------------------------
```

Table 9: Prevalence of Rearrest and Reincarceration: Essential Heterogeneity, Average, and Marginal Prison Peer Effects

Rearrest and Reincarceration: Heterogeneity and Prison Peer Effect Estimates				
	Unobserved Heterogeneity and Average Prison Peer Effects			
		Coefficient	Bootstrap SE	p
Rearrested	*IV = % Open Beds, Cellie Time In, Same Race & County*			
	UH (rho)	-0.1878	0.0740	0.011
	APPE	-0.0682	0.0836	0.414
Reincarcerated	*IV = % Open Beds, Cellie Time In, Same Race & County*			
	UH (rho)	-0.1899	0.0788	0.016
	APPE	-0.0665	0.0781	0.394
Rearrested OR	*IV = % Open Beds, Cellie Time In, Same Race & County*			
Reincarcerated	UH (rho)	-0.1572	0.0792	0.047
	APPE	-0.0646	0.0935	0.489
Rearrested AND	*IV = % Open Beds, Cellie Time In, Same Race & County*			
Reincarcerated	UH (rho)	-0.2204	0.0865	0.011
	APPE	-0.0701	0.0746	0.347
D= Cellmate Prior Incarceration				

Table 10: Switching Effects: Essential Heterogeneity, Average, and Marginal Prison Peer Effects

Switching Prison Peer Effect Estimates (Cellie Had Prior Arrest for Crime Type, Releasee Did Not)					
		Unobserved Heterogeneity and Average Prison Peer Effects			
			Coefficient	Bootstrap SE	p
Type P Crimes	Drug n=3,415*	*IV = % Open Beds, Cellie Time In, Same Race*			
		UH (rho)	0.0677	0.0622	0.276
		APPE	0.0372	0.0636	0.558
		Includes cubic terms			
		UH (rho)	NA	NA	NA
		APPE	0.1144	0.1091	0.294
Type Q Crimes	Contempt n=7,310*	*IV = % Open Beds, Cellie Time In*			
		UH (rho)	-0.0484	0.0890	0.587
		APPE	-0.0273	0.0951	0.774
		IV = % Open Beds, Cellie Time In, Same County			
		UH (rho)	-0.0411	0.0840	0.624
		APPE	-0.0147	0.0771	0.849
	Drugs n=3,409*	*IV = % Open Beds, Cellie Time In, Same Race*			
		UH (rho)	0.0731	0.0529	0.166
		APPE	0.0384	0.0561	0.494
		Includes cubic terms			
		UH (rho)	NA	NA	NA
		APPE	0.1051	0.0892	0.239
	Homicide n=9,229*	*IV = % Open Beds, Cellie Time In, Same Race*			
		UH (rho)	-0.0562	0.0310	0.069
		APPE	-0.0589	0.0298	0.048
	Robbery n=7,551*	*IV = % Open Beds, Cellie Time In, Same Race*			
		UH (rho)	-0.1674	0.0607	0.006
		APPE	-0.1659	0.0681	0.015

* Switching effects are possible only for releasees who do not have any prior offenses of the specified crime type

Table 11: Reinforcing Effects: Essential Heterogeneity, Average, and Marginal Prison Peer Effects

Reinforcing Prison Peer Effect Estimates (Cellie and Releasee Had Prior Arrest for Crime Type)					
		Unobserved Heterogeneity and Average Prison Peer Effects			
			Coefficient	Bootstrap SE	p
Type P Crimes	Drug n=6,701*	*IV = % Open Beds, Cellie Time In, Same Race*			
		UH (rho)	0.0680	0.0522	0.193
		APPE	0.0350	0.0546	0.522
		IV = % Open Beds, Cellie Time In, Same County			
		UH (rho)	0.0735	0.0758	0.333
		APPE	0.0512	0.0560	0.360
	Inchoate n=4,799*	*IV = % Open Beds, Cellie Time In, Same Race*			
		UH (rho)	-0.0912	0.0786	0.246
		APPE	-0.0147	0.0745	0.843
		IV = % Open Beds, Cellie Time In, Same County			
		UH (rho)	-0.0176	0.0688	0.798
		APPE	0.0550	0.0640	0.391
Type Q Crimes	Assault n=5,561*	*IV = % Open Beds, Cellie Time In, Same Race*			
		UH	-0.0484	0.1638	0.768
		APPE	0.0054	0.1950	0.978
	Drugs n=6,707*	*IV = % Open Beds, Cellie Time In, Same Race*			
		UH (rho)	0.0735	0.0714	0.304
		APPE	0.0357	0.0549	0.515
		IV = % Open Beds, Cellie Time In, Same County			
		UH (rho)	0.0783	0.0696	0.261
		APPE	0.0500	0.0480	0.298
	Car Theft n=1,799*	*IV = % Open Beds, Cellie Time In, Same Race*			
		UH (rho)	0.0006	0.0424	0.989
		APPE	0.0869	0.0491	0.077
	Weapons n=3,593*	*IV = % Open Beds, Cellie Time In, Same Race*			
		UH (rho)	0.0210	0.0708	0.767
		APPE	0.1446	0.0586	0.014

* Reinforcing effects are possible only for releasees who have at least one prior offense of the specified crime type

Table 12: Tests for Essential Heterogeneity (Heckman et al., 2006)

Compared models: ps1=baseline (no higher order or interaction terms); ps2=squared propensity score added; ps3=cubed propensity score added; ps4=quartic propensity score added; ps5=baseline+interaction terms; ps6=squared propensity score added; ps7=cubed propensity score added; ps8=quartic propensity score added

Rearrest

test	sig	df	LRT stat	NOBS
ps1 v. ps2	.8600362092004954	1	.0310915890058823	10116
ps2 v. ps3	.705088537706251	1	.1432323440712935	10116
ps3 v. ps4	.501449214378743	1	.4518679765551497	10116
ps1 v. ps5	.2547851704606596	260	274.6415018157477	10116
ps5 v. ps6	.1161809575765176	1	2.468063876867745	10116
ps6 v. ps7	.3898957211172212	1	.7392672003588814	10116
ps7 v. ps8	.9564436831125283	1	.0029830045987183	10116

Reincarceration

test	sig	df	LRT stat	NOBS
ps1 v. ps2	.1405971666718432	1	2.17141137689574	10116
ps2 v. ps3	.3891997635903628	1	.7414406920725014	10116
ps3 v. ps4	.7666424064769292	1	.0880722029705794	10116
ps1 v. ps5	.0206759846596102	260	308.5970718454064	10116
ps5 v. ps6	.9543059308055678	1	.0032833316563483	10116
ps6 v. ps7	.5861736528836656	1	.2963596378922375	10116
ps7 v. ps8	.8408795392536221	1	.0403080190881155	10116

Switching

::::::::::::::
Contempt
::::::::::::::

test	sig	df	LRT stat	NOBS
ps1 v. ps2	.0798343490436193	1	3.068270806252428	7310
ps2 v. ps3	.4100953974873065	1	.6785241324129174	7310
ps3 v. ps4	.8700298180389104	1	.0267717043882953	7310
ps1 v. ps5	.3623311798215359	253	260.3276936744969	7310
ps5 v. ps6	.5547143943141903	1	.3489389249592705	7310
ps6 v. ps7	.689919781642485	1	.1591722179144739	7310
ps7 v. ps8	.6357571760268337	1	.2243341459277346	7310

::::::::::::::
Drugs
::::::::::::::

test	sig	df	LRT stat	NOBS
ps1 v. ps2	.0350970308407279	1	4.440448278415715	3409
ps2 v. ps3	.0128615666915938	1	6.188052278766236	3409
ps3 v. ps4	.1429822023804731	1	2.145567007108866	3409
ps1 v. ps5	.2010432567419437	243	261.246836960815	3409
ps5 v. ps6	.0950790462882868	1	2.786206798720968	3409
ps6 v. ps7	.0453164274382949	1	4.006824428601021	3409
ps7 v. ps8	.0758586155981615	1	3.151469572796714	3409

::::::::::::::
Homicide
::::::::::::::

test	sig	df	LRT stat	NOBS
ps1 v. ps2	.751339695903446	1	.1004087270321179	9229
ps2 v. ps3	.5801030313389026	1	.306068112151479	9229
ps3 v. ps4	.0937760702516983	1	2.808327943545009	9229
ps1 v. ps5	1.94666019780e-13	259	460.1450590954355	9229
ps5 v. ps6	.0844458389821353	1	2.977188591050435	9229
ps6 v. ps7	.6692802593764713	1	.1824451787269936	9229
ps7 v. ps8	.7578479607926467	1	.095053837807427	9229

::::::::::::::
Robbery
::::::::::::::

test	sig	df	LRT stat	NOBS
ps1 v. ps2	.1180372335513702	1	2.44317316969682	7551
ps2 v. ps3	.3863901617067944	1	.7502718923278735	7551
ps3 v. ps4	.4073633878573829	1	.6864825237316836	7551
ps1 v. ps5	1.57228115203e-11	257	437.3500882521148	7551
ps5 v. ps6	.4624258328276977	1	.5400166340878059	7551
ps6 v. ps7	.1097751864573328	1	2.557454807149043	7551
ps7 v. ps8	.8264772945867208	1	.0480581863093903	7551

::::::::::::::
Weapons
::::::::::::::

test	sig	df	LRT stat	NOBS
ps1 v. ps2	.2532354541031617	1	1.3053656109239	6538
ps2 v. ps3	.9048804402842443	1	.0142798879014663	6538
ps3 v. ps4	.4838457648565085	1	.4901828180175016	6538
ps1 v. ps5	1.04142161233e-08	265	414.9180458893534	6538
ps5 v. ps6	.1688046118142444	1	1.89352731134295	6538
ps6 v. ps7	.6298047589210243	1	.2323256112567833	6538
ps7 v. ps8	.4163602050926452	1	.6605659716760783	6538

```
::::::::::::::
Drugs (P)
::::::::::::::
test              sig               df    LRT stat          NOBS
ps1 v. ps2        .0460055251756574 1     3.981392146693679 3415
ps2 v. ps3        .0325508205444063 1     4.569249617356263 3415
ps3 v. ps4        .1420826049519345 1     2.155257681997682 3415
ps1 v. ps5        .1706476209710454 243   263.8865609268806 3415
ps5 v. ps6        .121508169589847  1     2.397772336901653 3415
ps6 v. ps7        .1128169489996114 1     2.514310769152758 3415
ps7 v. ps8        .0819424087177859 1     3.025948215091262 3415

::::::::::::::
Inchoate
::::::::::::::
test              sig               df    LRT stat          NOBS
ps1 v. ps2        .2198875892726277 1     1.505104691578254 5329
ps2 v. ps3        .4003231325714686 1     .7073554686594434 5329
ps3 v. ps4        .8048773692948943 1     .0610286967444154 5329
ps1 v. ps5        3.77873524269e-06 260   375.0577542354717 5329
ps5 v. ps6        .839436805798206  1     .0410524022813661 5329
ps6 v. ps7        .9912622792795239 1     .0001199315806844 5329
ps7 v. ps8        .546529583656248  1     .363571122670691 7 5329
```

Reinforcing

```
::::::::::::::
Drugs
::::::::::::::
test              sig               df    LRT stat                NOBS
ps1 v. ps2        .5431790743922587 1     .3696794001452872       6707
ps2 v. ps3        .6001751624062519 1     .2747317933772138       6707
ps3 v. ps4        .7638693611947969 1     .0902422888839283       6707
ps1 v. ps5        .0091077862919077 251   306.935011216272        6707
ps5 v. ps6        .6183769993251442 1     .2481552909703169       6707
ps6 v. ps7        .5458958189675083 1     .3647212051901079       6707
ps7 v. ps8        .5094180972776873 1     .4352622035303284       6707

::::::::::::::
Motor Vehicle Theft
::::::::::::::
test              sig               df    LRT stat                NOBS
ps1 v. ps2        .7486389201214209 1     .1026783159808815       1799
ps2 v. ps3        .5110697178830772 1     .4318762834257939       1799
ps3 v. ps4        .9081320385440725 1     .0133160070054998       1799
ps1 v. ps5        .0000441437420295 223   315.537636754947        1799
ps5 v. ps6        .9848856818255333 1     .0003588797467273       1799
ps6 v. ps7        .7407539739639279 1     .1094650662466847       1799
ps7 v. ps8        .4359377858064901 1     .6069519039584748       1799
```

::::::::::::::
Weapons
::::::::::::::

test	sig	df	LRT stat	NOBS
ps1 v. ps2	.5109989930090035	1	.4320208855210694	3593
ps2 v. ps3	.1464060397376189	1	2.10930245823738	3593
ps3 v. ps4	.980999635279627	1	.0005671864637407	3593
ps1 v. ps5	.0982642565547843	241	269.7647420208332	3593
ps5 v. ps6	.5576862251785658	1	.343726234292717	3593
ps6 v. ps7	.1658445323701795	1	1.920110019490494	3593
ps7 v. ps8	.2642883174978843	1	1.246153990829498	3593

::::::::::::::
Assault
::::::::::::::

test	sig	df	LRT stat	NOBS
ps1 v. ps2	.3467647008951087	1	.8852612582741131	5561
ps2 v. ps3	.2028509763079334	1	1.621728248436739	5561
ps3 v. ps4	.1020823598959257	1	2.672705461322948	5561
ps1 v. ps5	.0520590501099049	246	283.1071372294709	5561
ps5 v. ps6	.1391406071302318	1	2.187437764729111	5561
ps6 v. ps7	.1373657769871136	1	2.207222675974663	5561
ps7 v. ps8	.7951569126876066	1	.0674025408616217	5561

::::::::::::::
Drugs (P)
::::::::::::::

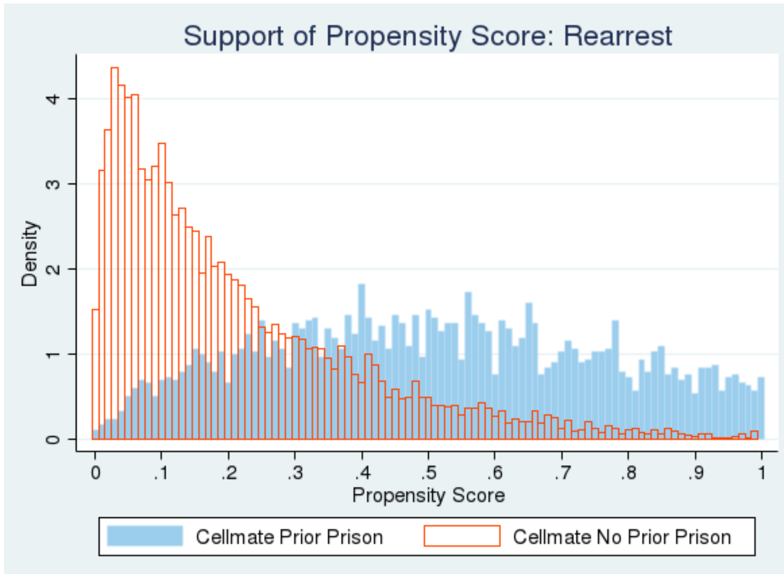
test	sig	df	LRT stat	NOBS
ps1 v. ps2	.530950958302818	1	.392571197401594	6701
ps2 v. ps3	.594590857669431	1	.2832316531794277	6701
ps3 v. ps4	.6948860900952104	1	.1538466977799544	6701
ps1 v. ps5	.0065281770572356	251	310.0432171393031	6701
ps5 v. ps6	.5314454984472958	1	.3916268484917964	6701
ps6 v. ps7	.5570395785987636	1	.3448559820844821	6701
ps7 v. ps8	.4610103345358335	1	.5434405590931419	6701

::::::::::::::
Inchoate
::::::::::::::

test	sig	df	LRT stat	NOBS
ps1 v. ps2	.3856742523046426	1	.7525367974990331	4799
ps2 v. ps3	.7630651064031611	1	.0908770569762964	4799
ps3 v. ps4	.6177533310926748	1	.2490379094429045	4799
ps1 v. ps5	.6059448683540808	245	238.4417784870866	4799
ps5 v. ps6	.8221385531009088	1	.0505329092579814	4799
ps6 v. ps7	.960030202342561	1	.0025115816665675	4799
ps7 v. ps8	.7726140469963159	1	.0834963264824182	4799

FIGURES

Figure 1: Rearrest: Propensity Score Support and Treatment Effects (D = Cellmate Prior Incarceration)



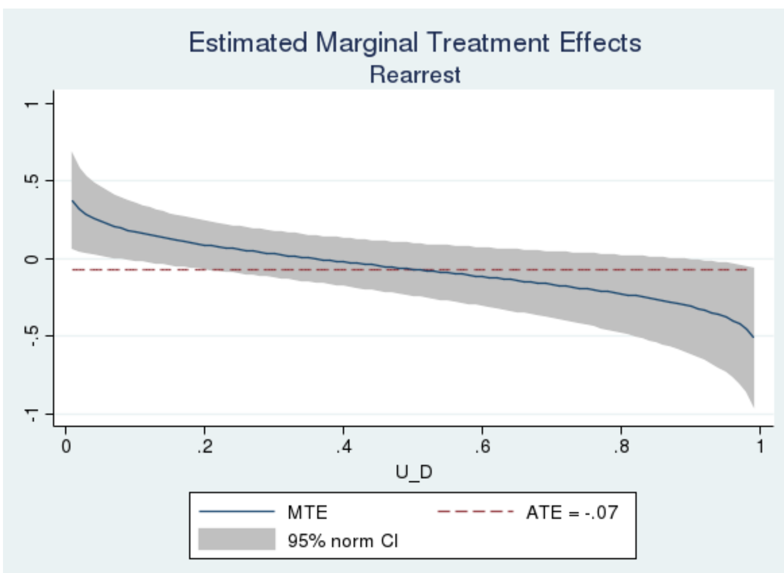
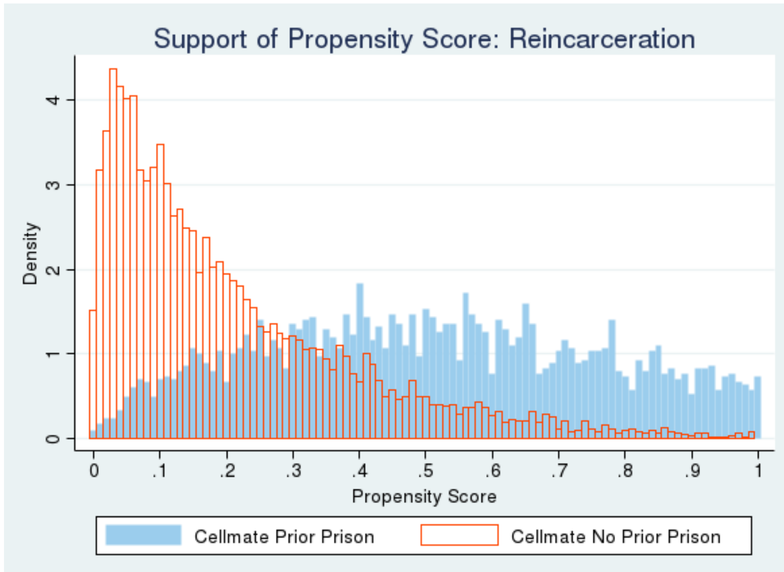


Figure 2: Reincarceration: Propensity Score Support and Treatment Effects (D = Cellmate Prior Incarceration)



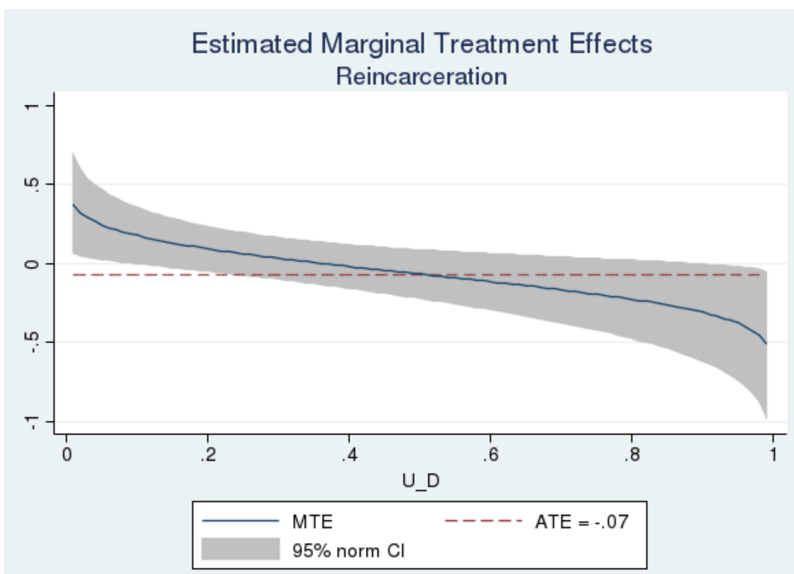
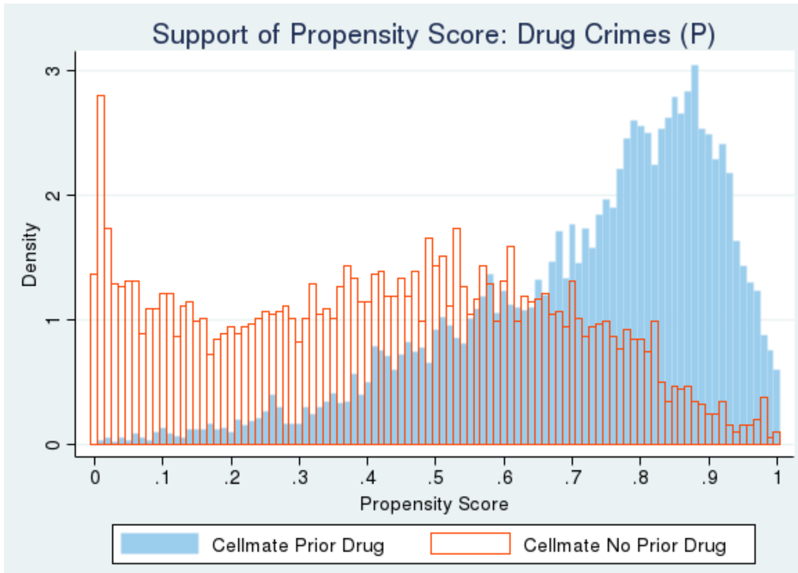


Figure 3: Switching: Propensity Score Support and Treatment Effects, Drug Crimes (Type P)



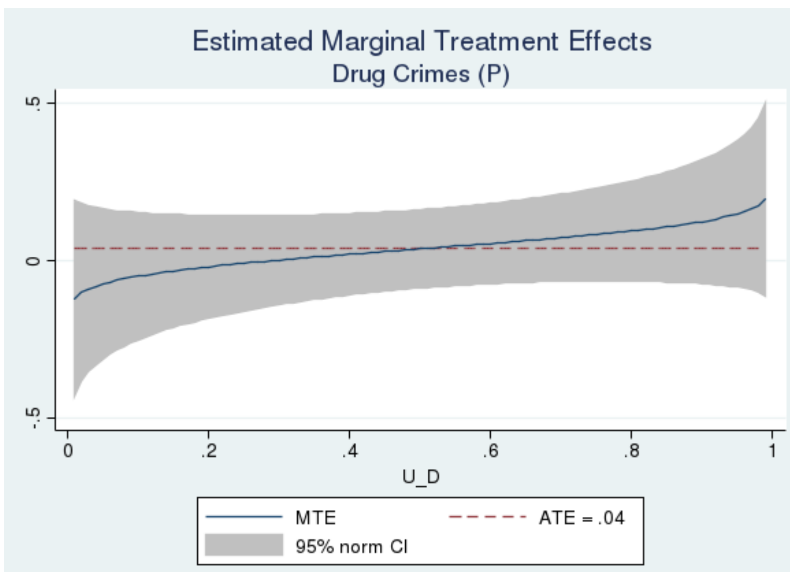
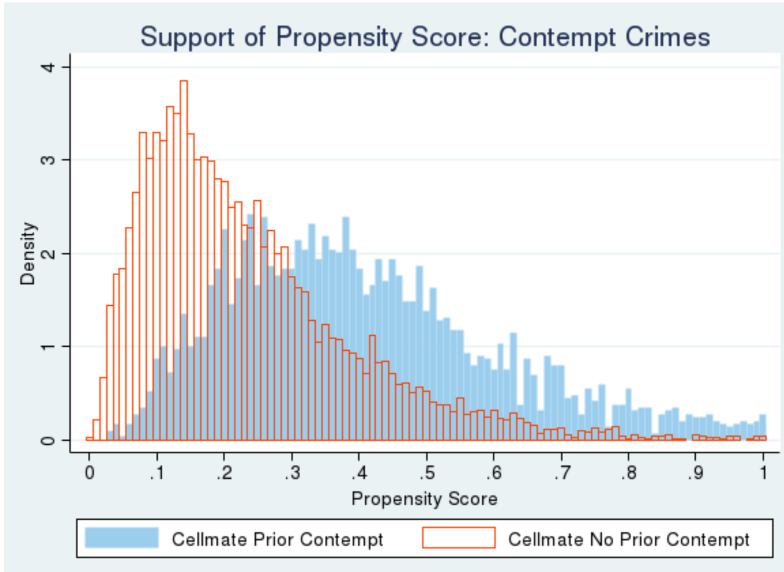


Figure 4: Switching: Propensity Score Support and Treatment Effects, Contempt Crimes



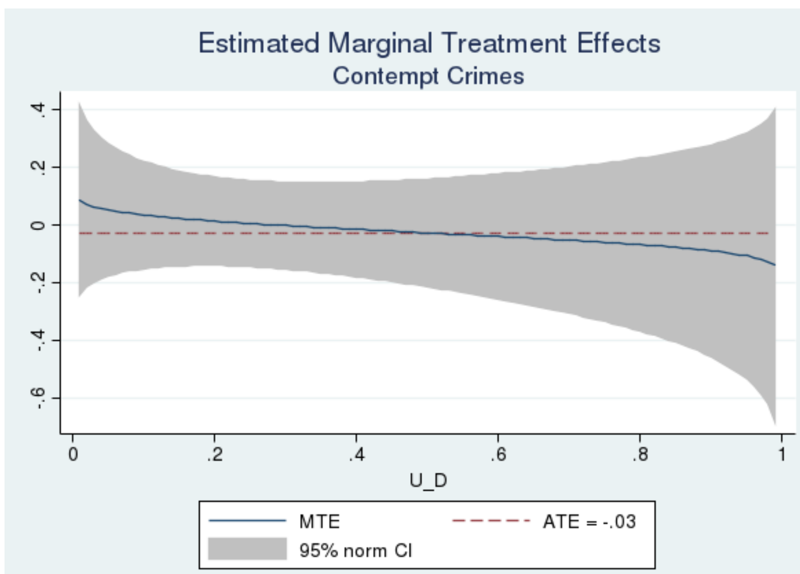
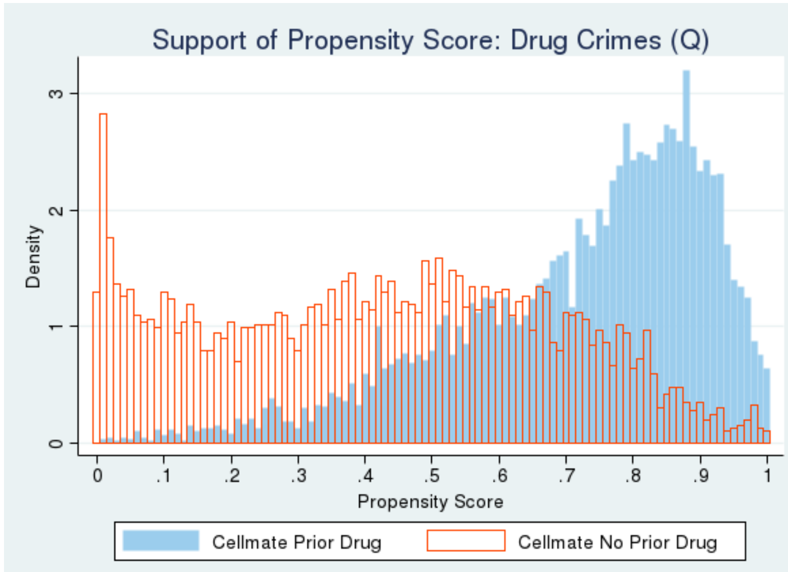


Figure 5: Switching: Propensity Score Support and Treatment Effects, Drug Crimes (Type Q)



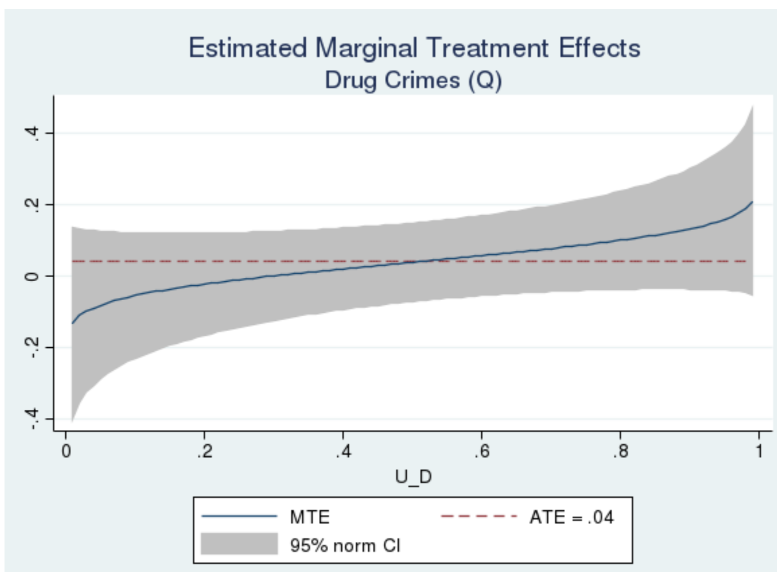
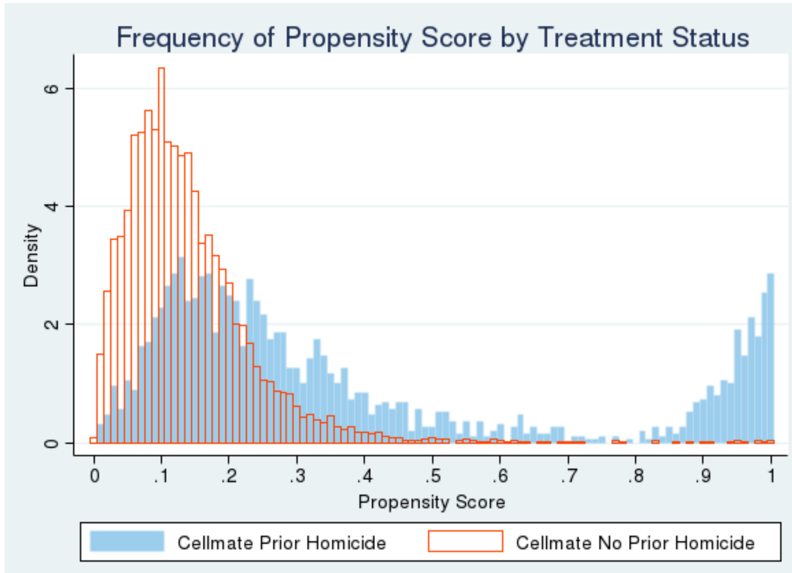


Figure 6: Switching: Propensity Score Support and Treatment Effects, Homicide



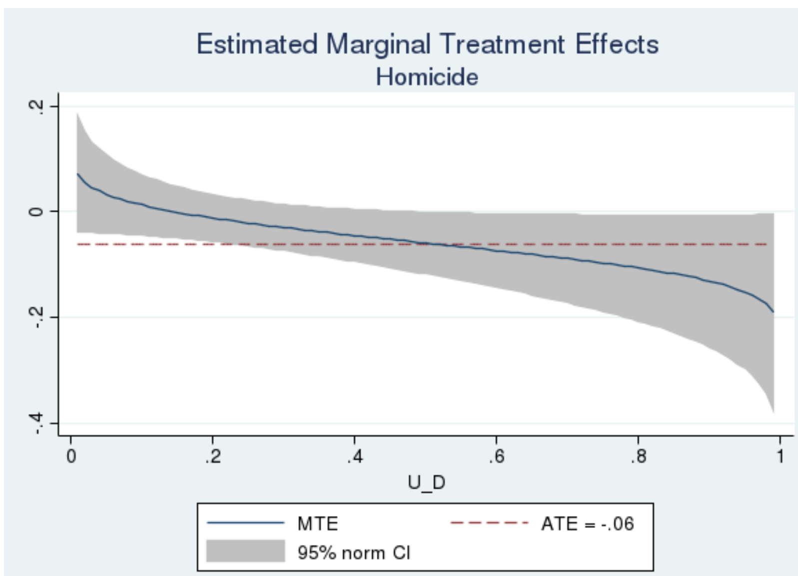
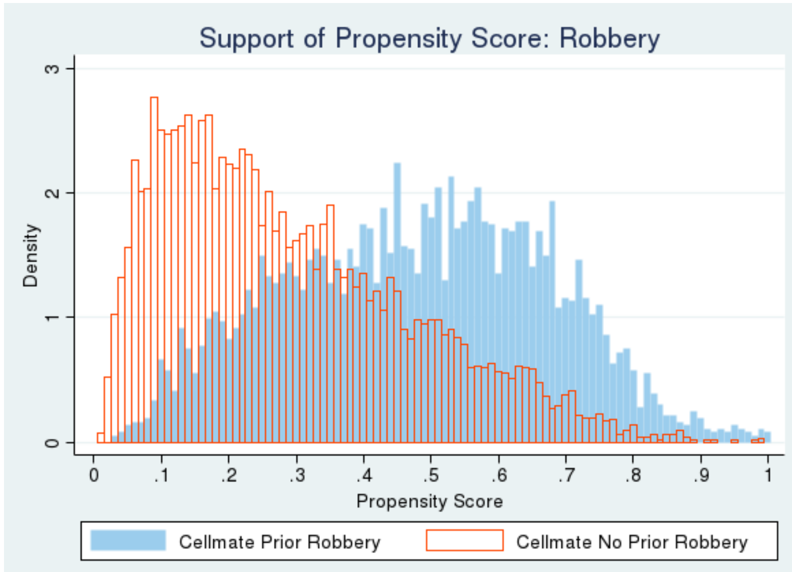


Figure 7: Switching: Propensity Score Support and Treatment Effects, Robbery



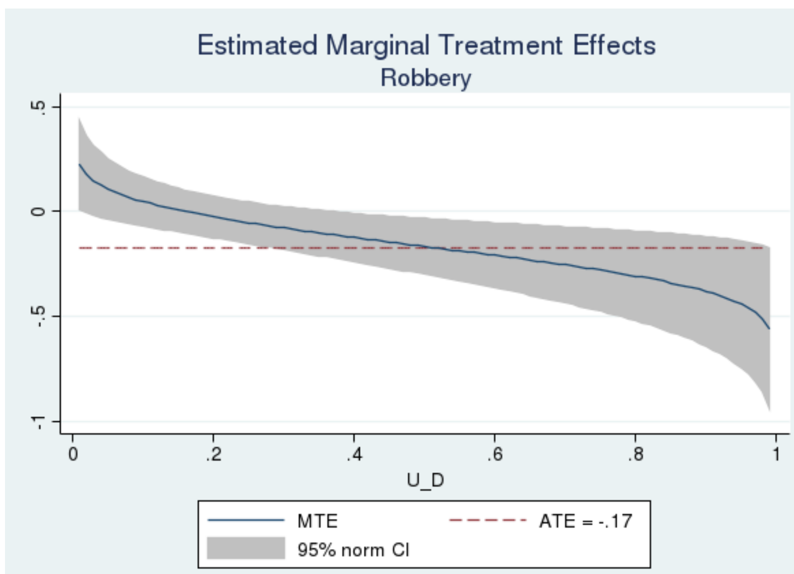
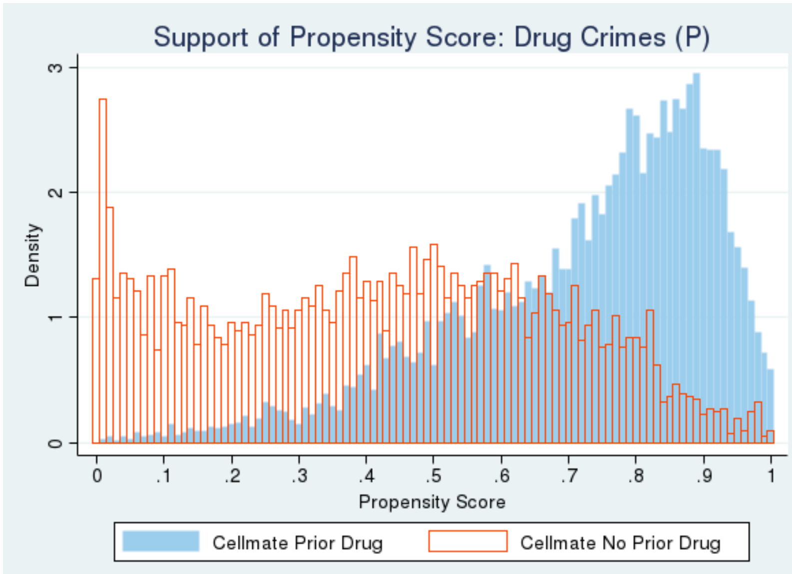


Figure 9: Reinforcing: Propensity Score Support and Treatment Effects, Drug Crimes (Type P)



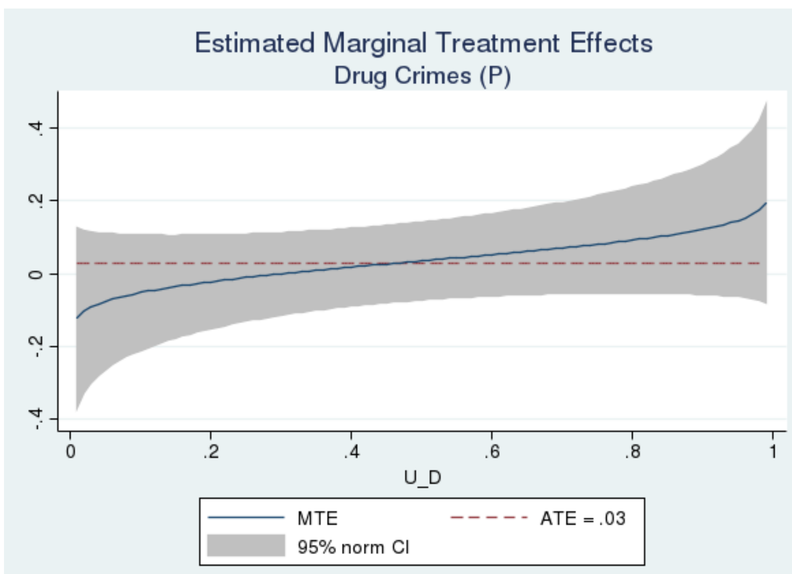
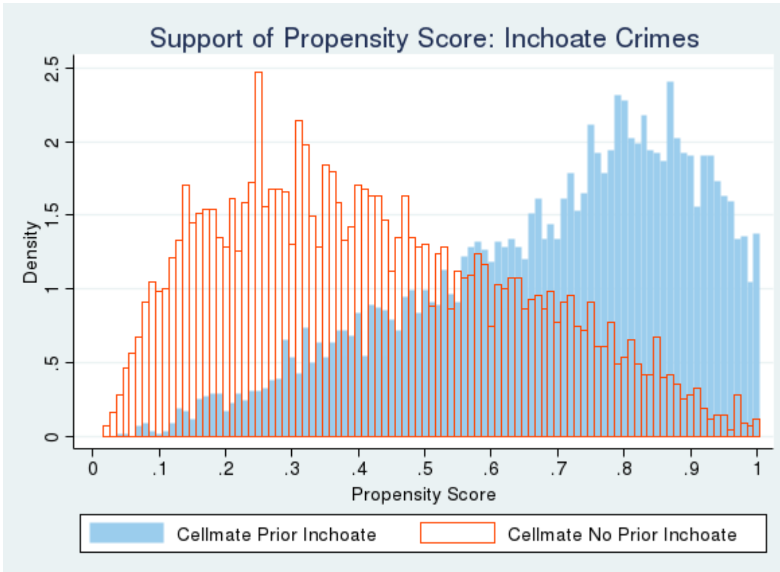


Figure 10: Reinforcing: Propensity Score Support and Treatment Effects, Inchoate



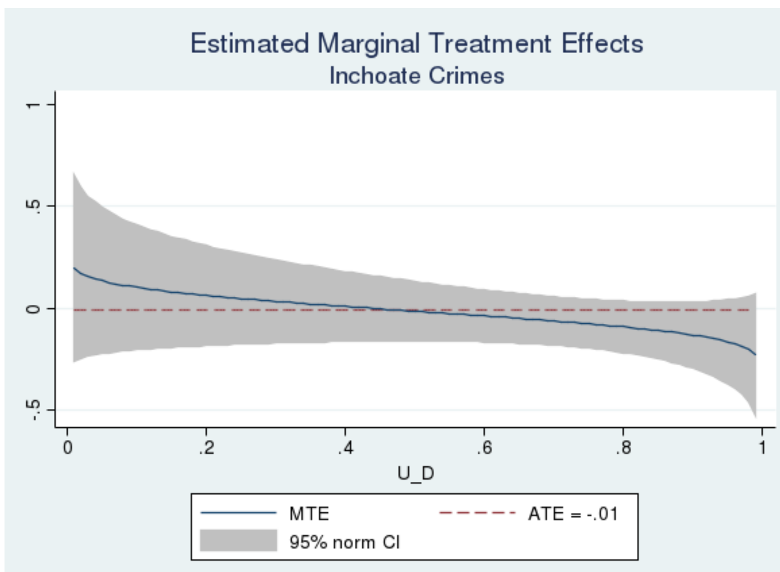
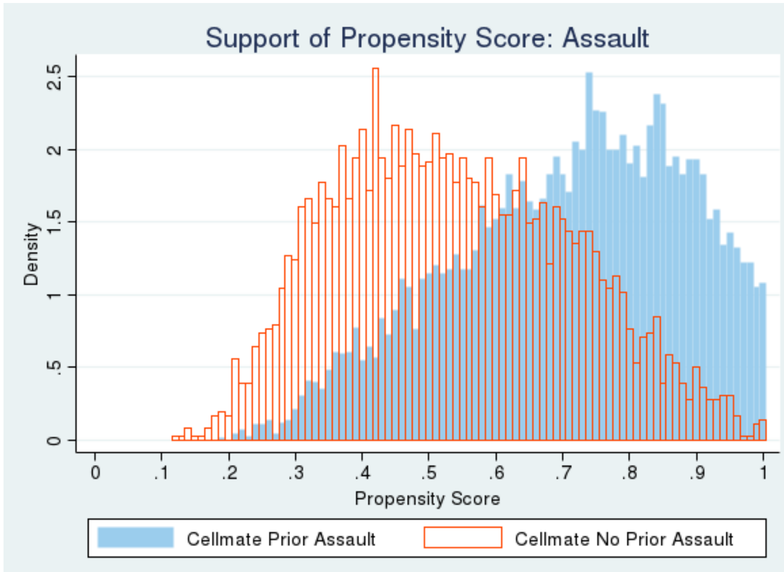


Figure 11: Reinforcing: Propensity Score Support and Treatment Effects, Assault



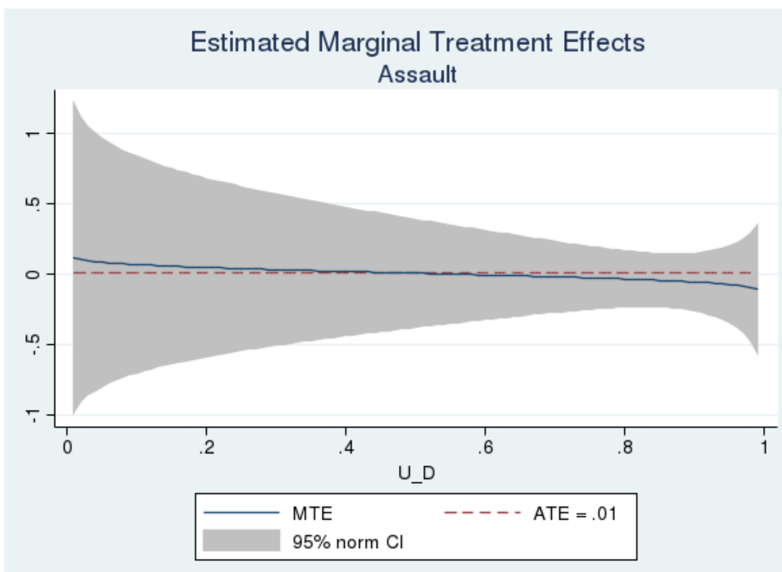
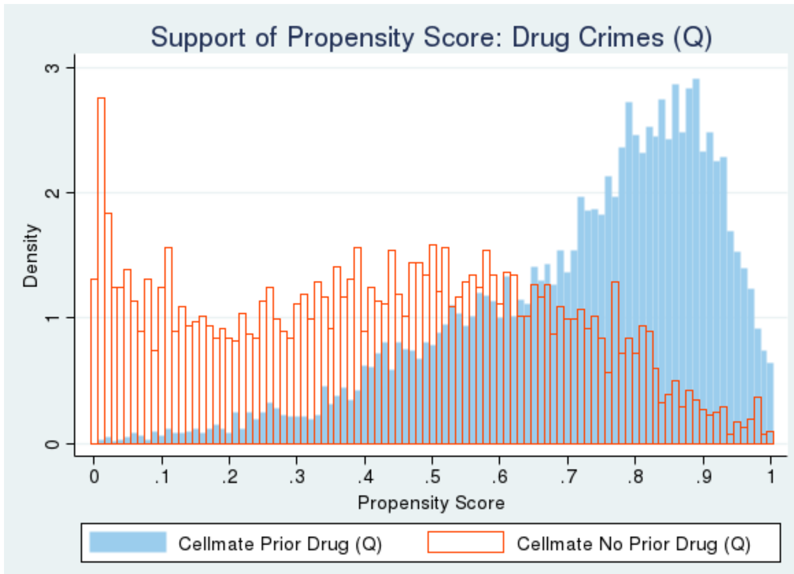


Figure 12: Reinforcing: Propensity Score Support and Treatment Effects, Drugs (Type Q)



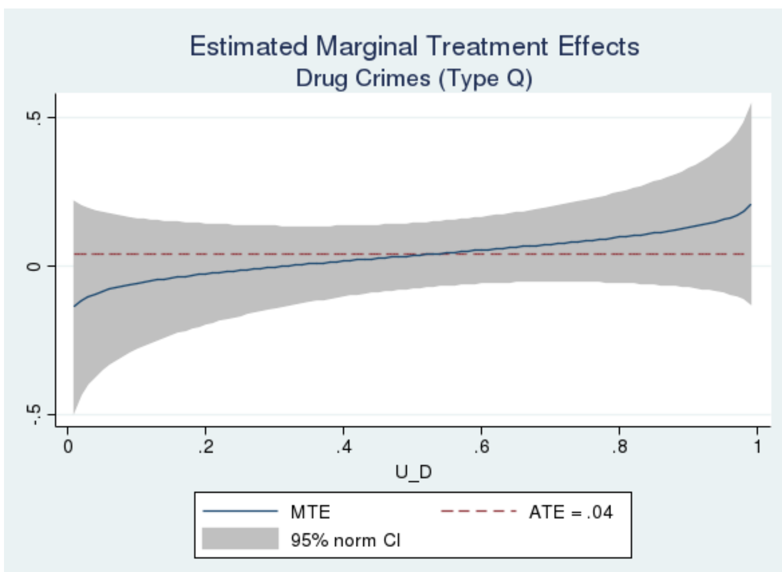
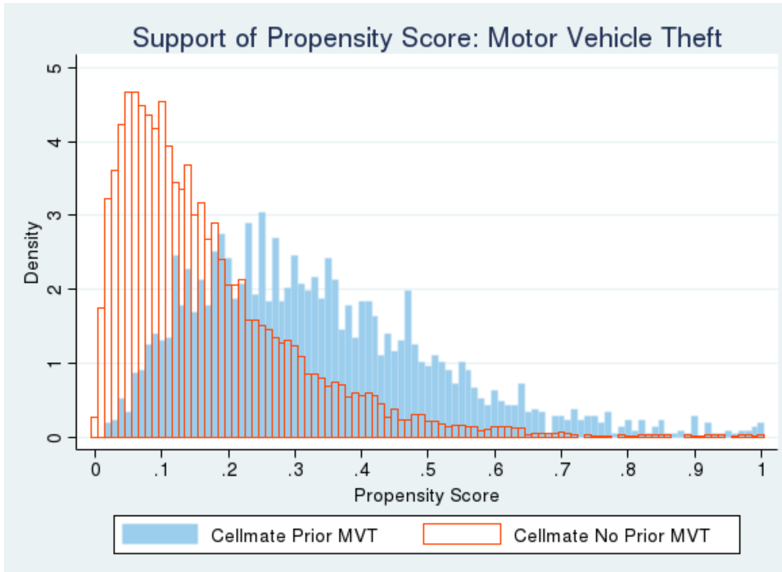


Figure 13: Reinforcing: Propensity Score Support and Treatment Effects, Motor Vehicle Theft



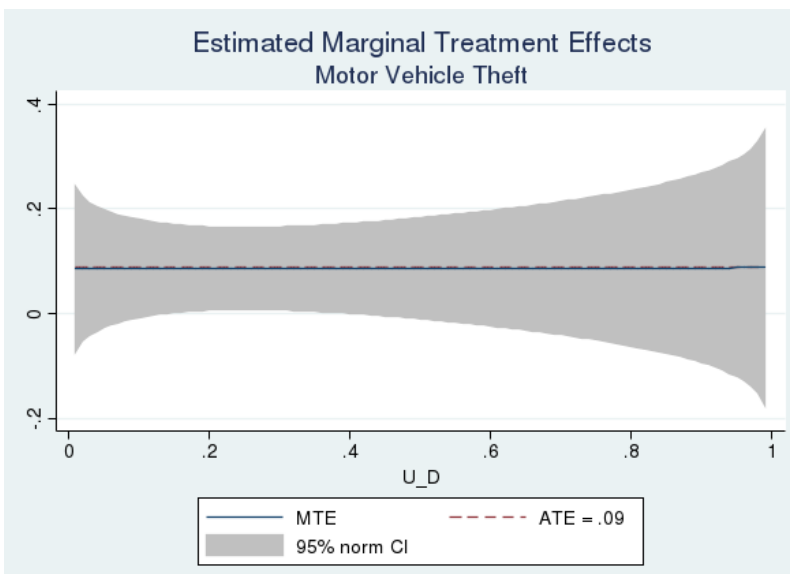
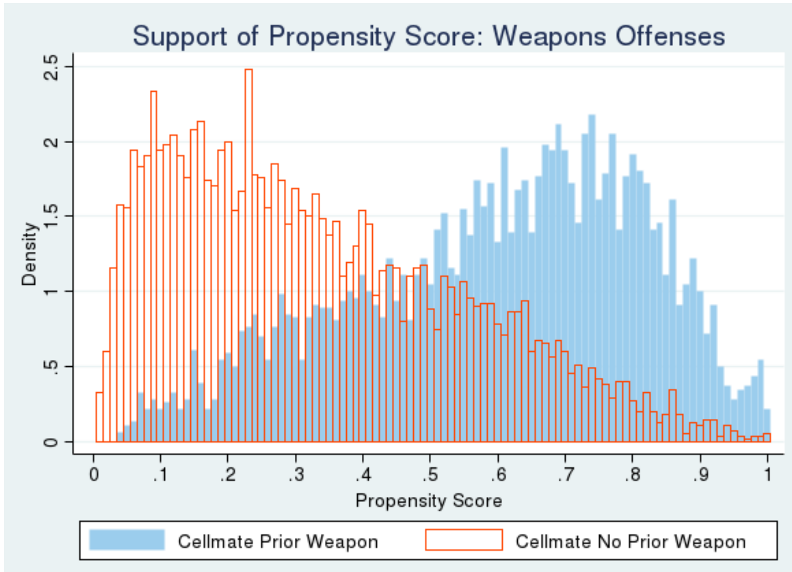
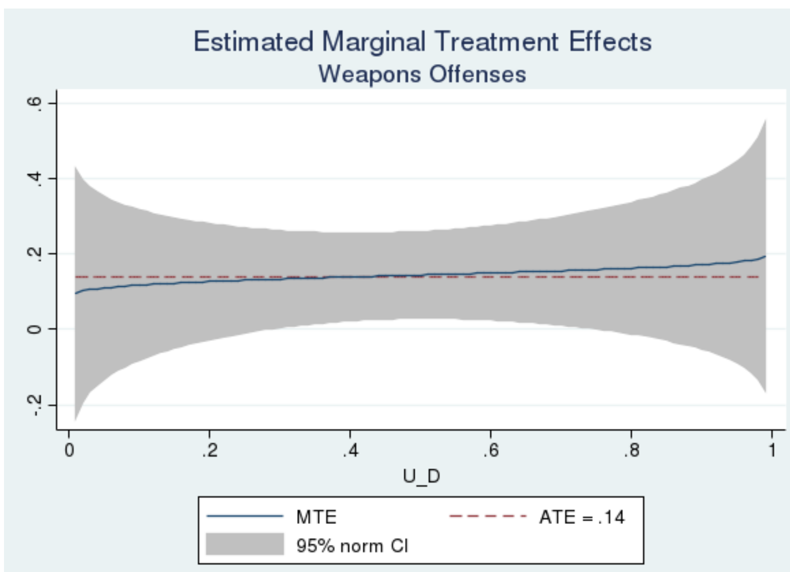


Figure 14: Reinforcing: Propensity Score Support and Treatment Effects, Weapons





APPENDIXES

Appendix A: Local Instrumental Variables Assumptions

In a potential outcomes (Fisher, 1935; Roy, 1951; Cox, 1958; Rubin, 1978) framework, that assesses the role of a single treatment in producing two average outcomes, one for the treated individuals and one for the untreated individuals, the two potential outcomes can be denoted Y_{0i} and Y_{1i} . They take the following forms:

$$Y_1 = \mu_1(X) + U_1 \; and \; Y_0 = \mu_0(X) + U_0$$

where characteristics X are observed by the researcher and the decision maker and characteristics U are certainly unobserved by the researcher, but may or may not be known to the decision maker.

If $D_i = 0$ denotes the untreated case and $D_i = 1$ denotes the treated case, the realization of the outcome Y_i for each individual is:

$$Y_i = D_i Y_{1i} + (1 - D_i) Y_{0i}$$

Heckman and Vytlacil (1999) assume that a latent variable model determines the decision maker's treatment condition. The latent variable D^* depends on Z_i, observed, and U_{Di}, unobserved, random variables and takes the form:

$$D_i^* = \mu_D(Z_i) - U_{Di},$$
$$where \; D_i = 1 \; if D_i^* \geq 0 \; and \; D_i = 0 \; otherwise$$

This is the basic model, which requires the following assumptions to be identified:

A1. Y_{0i} and Y_{1i} are defined for everyone, meaning there are realizations of both outcomes stemming from both treatments in the study sample.

A2. Y_0 and Y_1 have finite first moments, meaning Y_0 and Y_1 have realizable mean values.

A3. Y_{0i} and Y_{1i} are independent across decision makers, such that the stable unit treatment value assumption (SUTVA) applies (Cox, 1958).

A4. $\mu_D(Z)$ is a nondegenerate random variable conditional on $X = x$, which implies that $\mu_D(Z)$ is an exclusion restriction such that the instrument Z affects treatment D only through the endogenous regressor X (Imbens & Angrist, 1994).

A5. (U_D, U_0) and (U_D, U_1) are independent of (Z, X) (Imbens & Angrist, 1994).

A6. (U_D, U_0) and (U_D, U_1) are continuous with respect to Lebesgue measure on $\mathfrak{R}^2$.[16] This implies that U_D is distributed uniformly over the range between zero and one.

A7. $1 > Pr(D = 1|X) > 0$: the probability of being treated is well defined (i.e., there are both treated and untreated individuals and the probability of treatment does not exceed one or fall below zero for any individual).

A8. $X_0 = X_1$ almost everywhere. That is, the treated and control groups are observationally equivalent (i.e., comparable), such that there is "common support of the propensity score" (e.g., Rosenbaum & Rubin, 1983, 1984; Apel & Sweeten, 2010). The propensity score (i.e., propensity to be treated) defines to whom treatment effects apply. Common support of the propensity score means that for each propensity to be treated based on observables, there are people who both select into treatment and people who do not select into treatment.

[16] A Lebesque measure is the notion of length extended to more complicated sets (e.g., beyond the distance between two points). That is, if length is the distance between two points, a and b, or b-a, a Lebesque measure extends that notion to multiple dimensions. This assumption is, as Heckman and Vytlacil (2005) put it, "a technical assumption made primarily for expositional convenience" (p. 676). It is akin to assuming continuity in two dimensions or over a plane, thereby allowing for integration.

Appendix B: Bed Assignment Survey and Results

Thank you for taking the time to answer a few questions regarding the process by which inmates are placed in beds.

We are interested in better understanding how decisions to place inmates into cells are made. We are particularly interested in any factors, such as (but not limited to) custody level (PACT), risk level (RST/LSIR), inmate demographics (age, race, etc.), inmate personal preferences, separation issues, commitment crime types, and bed availability, that might affect inmate bed placements. We are interested in how important each of those factors is in the decision making process. We are also interested in the bed placement decision making process itself.

Please answer each of the questions as completely as possible. More information is better than less. Additionally, if you can, please attach copies of any official checklists, guidelines, or procedures that are used to place inmates.

Q1. Please describe how inmates are assigned to beds at different levels of your institution (e.g., building, section, cell). Please provide as much information as you think necessary to fully describe the placement process, keeping in mind that we are especially interested in the factors that determine inmate placements and how those factors are weighted (i.e., how important each of the factors is). For this question, we are interested in the process that applies to the general population, that is, most of your inmates. For example, the procedure may attempt to double-cell inmates if their commitment crime types are similar, their custody levels are the same, and there is no separation issue between them. Or, the procedure may assign inmates of the same custody level to one building, but within the building, inmates are assigned to cells based on bed space availability.

If you have official guidelines, checklists, or procedures that dictate how inmates are assigned to cells in your facility, please attach the documentation that describes the procedures.

Q2. Is the process used to place inmates the same throughout your facility or does it differ by building or section within your facility? If some buildings or sections in your facility place inmates using a different process, could you please describe the different processes, indicating to which building or section they apply? (Here, we are interested in any special cases that might exist.)

Q3. Why are inmates generally moved from cell to cell during their stays in your institution? Could you please list some reasons for inmate moves (e.g., changes in custody level) and indicate how common they are?

Q4. Who is responsible for overseeing the inmate placement process? If we may contact him/her with further questions, please provide his/her contact information.

Results: Factors in PADOC initial placements

Shaded "1" indicates the factor is considered

	Facilities																									
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
Inmate characteristics																										
Race	1	.	1	.	1	.	1	1	1	1	1	1	1	1	.	1	1	.	1	1	.	.	.	1	.	.
Age	.	.	1	.	1	1	1	1	1	.	1	1	.	1	1	1	1	.	1	1	.	.	.	1	.	1
Stature/Size	.	.	1	.	1	1	.	1	.	.	.	.	1	.	1	.	1	1	.	.	.	.	.	.	.	.
Sexual orientation	.	.	.	.	1	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.
Religion	1	.	.	.	.	.	.	.	1	.	.	.	1	1	.	.	.	.	1	.	.	.	.	.	.	.
Temperament/Personality	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	1	1	1	.	.	.	.	.	.	1
Hygiene	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Smoking preference	.	.	.	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.
Family members	.	.	.	.	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	1	.
Geographic origin	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.
Commit status	.	.	1	.	1	.	1	1	.	.	.	.	.	.	1	.	.	.	1	1	.	.	.	.	1	1
Criminal/incarceration																										
Current offense	.	.	1	.	1	.	.	.	.	.	1	.	.	.	.	1	1	1	.	1	.	1	.	.	.	.
Sentence/Time to min	1	1	1	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	1	1	.	.	.	.	.	.
Criminal/incarceration history	.	.	.	.	.	1	.	.	1	.	1	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.
Number of previous cellmates	.	.	.	.	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	.
Code characteristics																										
Medical	1	1	1	.	1	1	1	.	1	.	1	1	1	1	1	1	1	1	1	1	1	1	1	1	.	1
Mental	.	1	1	.	.	.	1	.	1	1	1	.	1	1	1	.	.	1	1	1	.	1	1	1	1	.
Program	1	1	1	1	1	1	1	1	.	1	.	1	1	1	1	1	1	1	.	1	1	1	1	1	1	1
Work	.	.	1	.	.	1	.	1	1	1	.	.	.	.	1	1	.	1	1	.	.	.	1	.	1	.
Housing	.	.	.	.	1	1	1	.	.	.	.	.	1	1	1	.	.	1	1	.	.	1	.	1	.	.
Risk	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Security	.	.	.	.	.	.	.	.	.	.	1	.	1	1	.	1	.	1	.	.	.	.	.	.	.	.
Gang	1	.	1	.	1	1	1	.	1	.	1	.	1	1	.	.	.	.	1	.	.	.	.	1	.	.
Victim/Predator	1	.	.	.	.	1	1	.	1	.	.	1	1	1	1	.	.	1	1	.	.	.	.	1	.	.
Escape	.	.	.	.	1	.	1	1	1	.	1	.	1	.	.	.	.	1	.	.	.	.	.	.	.	.
Behavior	.	1	1	.	1	1	1	.	1	.	.	.	.	1	.	.	.	.	1	1	.	.	.	1	1	.
Custody level	1	1	1	.	.	1	1	1	1	.	1	1	1	.	1	1	1	.	1	1	.	1	1	1	.	.
O code	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Separations/Preferences																										
Administrative separation	.	.	.	.	1	.	1	.	.	.	.	.	1	1	1	.	.	.	.	1	.	1	.	.	1	1
Informal separation	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.
Inmate agreement	.	.	.	1	.	1	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Inmate request/preference	1	.	.	.	.	.	1	.	1	.	1	.	.	1	1	.	.	.	.	.	.	.	1	.	.	.
Facility characteristics																										
Design	.	.	.	.	.	1	1	1	.	.	.	.	1	.	1	1	1	.	.	.	.	.	.	.	1	.
Bed space	.	.	1	.	1	.	1	1	.	1	1	1	.	1	1	1	.	1	1	1	.	1	1	1	1	1
Block custody level ratio	.	.	.	.	1	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.
Counselor case load	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	1	.	.
Unit manager override	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.

Results: Factors in PADOC within-facility moves

Shaded “1” indicates the factor is considered

	Facilities																									
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
Inmate requests																										
Inmate agreement	.	.	.	1	.	1	1	.	1	.	.	.	.	1	1	1	.	.	1	1	.	.	1	1	.	.
Inmate preference	1	1	1	.	.	.	1	.	.	1	1	1	.	.	.	.	.	.	1	.	.	1	.	.	1	1
Formal separations	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Local separation	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	1	.	1	.	.
Security & Behavior																										
Security	1	1	.	.	.	.	1	1	1	1	.	.	1	.	1	1	.	.	.	.	.	1	1	.	1	.
Escape	.	.	.	.	1	.	.	.	.	1	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.
Incompatibility	.	.	1	1	.	.	1	1	.	.	.	.	.	1	.	.	1	.	1	1	.	1	.	.	1	1
Relationship issues	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.
Negative adjustment	.	.	1	.	1	.	1	.	.	1	1	.	1	.	1	1	.	.	1	.	1	.	.	.	.	.
Positive adjustment	.	.	.	.	.	.	1	.	1	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	.	1
Staff/inmate conflict	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Status changes																										
Medical	.	.	1	1	1	1	.	.	.	1	1	1	1	.	1	1	1	1	1	1	1	.	1	1	.	.
Mental health	.	.	.	.	.	.	.	.	.	.	1	.	.	.	1	1	.	.	.	.	.	.	1	.	.	.
Program	1	1	1	.	1	1	.	1	.	1	1	.	1	.	1	.	1	1	.	1	.	.	1	1	.	.
Work	.	.	1	.	.	1	.	1	.	.	1	.	.	.	1	1	.	.	.	.	.	1	.	.	1	.
Custody level	.	.	1	.	.	1	.	.	.	1	.	1	1	.	.	1	1	.	.	.	.	.	.	.	.	.
Housing	.	.	.	1	1	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Institutional issues																										
Institutional needs	.	.	1	.	.	.	1	.	.	.	.	1	.	.	.	1	.	.	.	.	1	.	.	.	1	.
Bed space	.	.	.	.	.	.	.	.	.	.	.	.	1	.	.	.	.	.	.	.	.	1	.	.	.	.
Sentence length	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	1	.	.	.	.

Appendix C: Crimes within Crime Types [XXX]

[Available upon request.]

Appendix D: *margte* Output (Select Models)

Outcome = Rearrest for Any Crime

```
Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                     Number of obs      =     10116
Treatment Model: Probit                         Replications       =        50
------------------------------------------------------------------------------
                 |   Observed   Bootstrap                         Normal-based
    r_has_postA  |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
Treated          |
      r_staytime |   6.07e-06   .0000357     0.17   0.865     -.000064    .0000761
        r_single |   .0343024   .0213517     1.61   0.108    -.0075462    .0761511
         r_black |   .0741915   .0394097     1.88   0.060    -.0030501    .1514331
        r_latino |   .0251682   .0409446     0.61   0.539    -.0550817    .1054181
         r_urban |   .0550943   .0217478     2.53   0.011     .0124693    .0977193
   r_18under_1arr |   .0803268   .0192529     4.17   0.000     .0425918    .1180617
          r_p_iq |   .0001734   .0006971     0.25   0.804    -.0011929    .0015396
      r_p_hsgrad |  -.0164884   .0198343    -0.83   0.406    -.0553629    .0223861
     r_p_had_job |   .0697071   .0208969     3.34   0.001     .0287498    .1106643
       r_p_usvet |  -.0078147    .034798    -0.22   0.822    -.0760176    .0603881
      r_p_medlim |   .0082331   .0272059     0.30   0.762    -.0450894    .0615556
  r_p_prob_sexual |  -.0155773   .0254079    -0.61   0.540    -.0653759    .0342213
  r_p_prob_escape |   .0349174   .0168355     2.07   0.038     .0019204    .0679145
     r_p_prob_mh |    .021484   .0198219     1.08   0.278    -.0173663    .0603343
 r_p_prob_drugalc |   .0801141   .0332799     2.41   0.016     .0148866    .1453416
         r_misAB |   .0372257   .0211695     1.76   0.079    -.0042657    .0787172
         r_had_tc |   .1249715   .0284493     4.39   0.000     .0692118    .1807312
      r_cust_gt3 |   .0116403   .0192282     0.61   0.545    -.0260463    .0493269
           r_age |  -.0109442   .0012843    -8.52   0.000    -.0134613    -.008427
       r_npriarr |   .0217417   .0023067     9.43   0.000     .0172207    .0262628
       r_maxsent |  -.0013613   .0002723    -5.00   0.000     -.001895   -.0008276
         c_lifer |   .0227795   .1374655     0.17   0.868     -.246648     .292207
        c_single |   .0005135   .0178477     0.03   0.977    -.0344674    .0354944
         c_black |  -.0151988   .0303272    -0.50   0.616    -.0746391    .0442415
        c_latino |  -.0076744   .0385784    -0.20   0.842    -.0832866    .0679378
         c_urban |  -.0032858   .0225089    -0.15   0.884    -.0474024    .0408308
   c_18under_1arr |   .0542495   .0211856     2.56   0.010     .0127264    .0957725
          c_p_iq |   .0003858    .000732     0.53   0.598    -.0010489    .0018206
      c_p_hsgrad |  -.0151344   .0209829    -0.72   0.471      -.05626    .0259913
     c_p_had_job |   .0217301    .013436     1.62   0.106    -.0046041    .0480643
       c_p_usvet |  -.0254921   .0359038    -0.71   0.478    -.0958623     .044878
      c_p_medlim |  -.0614286    .019473    -3.15   0.002     -.099595   -.0232622
  c_p_prob_sexual |  -.0191426   .0219708    -0.87   0.384    -.0622046    .0239194
  c_p_prob_escape |  -.0129596   .0171099    -0.76   0.449    -.0464943    .0205751
     c_p_prob_mh |   .0024794   .0218712     0.11   0.910    -.0403874    .0453461
 c_p_prob_drugalc |   .0368639   .0338295     1.09   0.276    -.0294407    .1031684
         c_misAB |   .0279081   .0317636     0.88   0.380    -.0343473    .0901636
         c_had_tc |  -.0313845   .0218215    -1.44   0.150    -.0741537    .0113848
      c_cust_gt3 |   .0159799   .0211868     0.75   0.451    -.0255454    .0575053
           c_age |   .0044172   .0023501     1.88   0.060     -.000189    .0090233
       c_npriarr |   .0034415   .0020494     1.68   0.093    -.0005751    .0074582
       c_maxsent |  -.0000525    .000067    -0.78   0.433    -.0001837    .0000788
     cp_hasPriorI |  -.0280347   .0466794    -0.60   0.548    -.1195247    .0634552
        cp_lifer |   -.160472   .2548389    -0.63   0.529    -.6599471    .3390031
       cp_single |  -.0254673   .0427262    -0.60   0.551    -.1092091    .0582744
        cp_black |   -.031489   .0489109    -0.64   0.520    -.1273526    .0643747
       cp_latino |  -.0599479   .0776221    -0.77   0.440    -.2120845    .0921887
        cp_urban |   .0637884   .0527714     1.21   0.227    -.0396418    .1672185
  cp_18under_1arr |   .0545575   .0346983     1.57   0.116    -.0134499    .1225649
         cp_p_iq |      -.001   .0015743    -0.64   0.525    -.0040856    .0020856
     cp_p_hsgrad |   .0466689   .0375223     1.24   0.214    -.0268734    .1202112
```

cp_p_had_job	-.061127	.0364423	-1.68	0.093	-.1325527	.0102986
cp_p_usvet	.0705064	.0677872	1.04	0.298	-.0623542	.2033669
cp_p_medlim	-.0613523	.0441277	-1.39	0.164	-.147841	.0251364
cp_p_prob_sexual	-.0213911	.0471696	-0.45	0.650	-.1138418	.0710596
cp_p_prob_escape	-.0156694	.0373225	-0.42	0.675	-.0888202	.0574813
cp_p_prob_mh	-.0060692	.0420141	-0.14	0.885	-.0884153	.0762769
cp_p_prob_drugalc	-.1127416	.0581165	-1.94	0.052	-.2266478	.0011647
cp_misAB	-.0097328	.0378718	-0.26	0.797	-.0839602	.0644946
cp_had_tc	-.0070128	.0451787	-0.16	0.877	-.0955615	.0815359
cp_cust_gt3	-.0427182	.04651	-0.92	0.358	-.1338762	.0484398
cp_age	-.0035629	.0022348	-1.59	0.111	-.007943	.0008172
cp_npriarr	-.0024405	.003017	-0.81	0.419	-.0083538	.0034728
cp_maxsent	.0000171	.0001104	0.16	0.877	-.0001992	.0002335
r_rel_q2	.046466	.0381205	1.22	0.223	-.0282489	.1211809
r_rel_q3	.0797545	.0395034	2.02	0.043	.0023292	.1571798
r_rel_q4	.05542	.0372511	1.49	0.137	-.0175909	.1284308
r_rel_q5	.0179436	.0345022	0.52	0.603	-.0496795	.0855667
r_rel_q6	.0458629	.0407961	1.12	0.261	-.0340959	.1258218
r_rel_q7	.0632872	.0414752	1.53	0.127	-.0180026	.144577
r_rel_q8	-.0029766	.0377849	-0.08	0.937	-.0770335	.0710804
tier_tt	.0208019	.0157102	1.32	0.185	-.0099896	.0515933
r_cell	.0284043	.0196385	1.45	0.148	-.0100864	.0668951
c_cell	.0148587	.0263655	0.56	0.573	-.0368167	.0665342
stretches	-.0003023	.0074553	-0.04	0.968	-.0149145	.0143098
r_time2rel	-.0000407	.0000304	-1.34	0.181	-.0001004	.0000189
pct_total_tt	.0010647	.000827	1.29	0.198	-.0005562	.0026856
numCellies	.000518	.0014453	0.36	0.720	-.0023148	.0033507
cellsqft_tt	-.0005914	.0010593	-0.56	0.577	-.0026676	.0014849
_Ifac_tt_52	-.0850722	.0511453	-1.66	0.096	-.1853151	.0151708
_Ifac_tt_54	-.1792722	.056834	-3.15	0.002	-.2906647	-.0678796
_Ifac_tt_55	-.0043695	.0550118	-0.08	0.937	-.1121906	.1034515
_Ifac_tt_56	-.0818028	.0636659	-1.28	0.199	-.2065856	.04298
_Ifac_tt_57	-.1265516	.056045	-2.26	0.024	-.2363978	-.0167054
_Ifac_tt_58	-.0405155	.0699325	-0.58	0.562	-.1775807	.0965497
_Ifac_tt_59	-.1233663	.0485839	-2.54	0.011	-.2185889	-.0281436
_Ifac_tt_60	-.0462319	.0568179	-0.81	0.416	-.1575928	.0651291
_Ifac_tt_61	-.0911986	.0791711	-1.15	0.249	-.2463711	.0639738
_Ifac_tt_62	-.1600168	.0645848	-2.48	0.013	-.2866007	-.0334329
_Ifac_tt_63	-.007912	.0788084	-0.10	0.920	-.1623735	.1465496
_Ifac_tt_64	-.0194546	.0485353	-0.40	0.689	-.1145821	.0756729
_Ifac_tt_65	-.0237458	.0580504	-0.41	0.682	-.1375225	.0900309
_Ifac_tt_66	-.0353021	.0830459	-0.43	0.671	-.1980691	.1274649
_Ifac_tt_68	-.0445487	.0441862	-1.01	0.313	-.1311521	.0420547
_Ifac_tt_69	-.1349877	.0815666	-1.65	0.098	-.2948554	.02488
_Ifac_tt_73	-.0512424	.0725206	-0.71	0.480	-.1933802	.0908955
_Ifac_tt_75	-.0864736	.0643734	-1.34	0.179	-.2126432	.039696
_Ifac_tt_76	-.0347113	.0519244	-0.67	0.504	-.1364813	.0670586
_Ifac_tt_77	-.0789082	.0551895	-1.43	0.153	-.1870777	.0292613
_Ifac_tt_78	-.0031383	.0545517	-0.06	0.954	-.1100576	.1037811
_Ifac_tt_81	-.1394869	.1030425	-1.35	0.176	-.3414465	.0624727
k	-.1090976	.0597889	-1.82	0.068	-.2262816	.0080864
_cons	.5772959	.3761378	1.53	0.125	-.1599207	1.314512
Untreated						
r_staytime	6.98e-06	.0000254	0.27	0.784	-.0000429	.0000568
r_single	.0216635	.0156518	1.38	0.166	-.0090135	.0523404
r_black	.0828589	.0212976	3.89	0.000	.0411164	.1246015
r_latino	-.0233179	.0228207	-1.02	0.307	-.0680456	.0214099
r_urban	.028599	.0120818	2.37	0.018	.004919	.0522789
r_18under_1arr	.069642	.0118147	5.89	0.000	.0464857	.0927983
r_p_iq	.0000147	.0004523	0.03	0.974	-.0008717	.0009011
r_p_hsgrad	-.0266711	.0115825	-2.30	0.021	-.0493725	-.0039698
r_p_had_job	.0756288	.0139329	5.43	0.000	.0483208	.1029367
r_p_usvet	-.0003171	.0262617	-0.01	0.990	-.051789	.0511549
r_p_medlim	-.0090659	.0134964	-0.67	0.502	-.0355184	.0173866
r_p_prob_sexual	-.0000812	.0186628	-0.00	0.997	-.0366596	.0364973
r_p_prob_escape	.0408258	.0128966	3.17	0.002	.015549	.0661026
r_p_prob_mh	.0248449	.0095274	2.61	0.009	.0061715	.0435182
r_p_prob_drugalc	.0434581	.0216859	2.00	0.045	.0009546	.0859616
r_misAB	.01804	.0176976	1.02	0.308	-.0166466	.0527267

r_had_tc	.1234307	.0134701	9.16	0.000	.0970298	.1498317
r_cust_gt3	.0439016	.0130388	3.37	0.001	.0183459	.0694572
r_age	-.0095737	.0007569	-12.65	0.000	-.0110571	-.0080903
r_npriarr	.0241255	.0017783	13.57	0.000	.02064	.027611
r_maxsent	-.001738	.0002221	-7.83	0.000	-.0021732	-.0013027
c_lifer	.0799707	.0552945	1.45	0.148	-.0284045	.188346
c_single	-.0126674	.0167616	-0.76	0.450	-.0455195	.0201848
c_black	-.003784	.018217	-0.21	0.835	-.0394887	.0319207
c_latino	.0086403	.0196974	0.44	0.661	-.0299659	.0472465
c_urban	-.0027242	.0141554	-0.19	0.847	-.0304682	.0250197
c_18under_1arr	-.00613	.012501	-0.49	0.624	-.0306314	.0183715
c_p_iq	-.0003057	.0003962	-0.77	0.440	-.0010822	.0004708
c_p_hsgrad	-.0237999	.0119376	-1.99	0.046	-.0471972	-.0004025
c_p_had_job	.0020316	.0135733	0.15	0.881	-.0245716	.0286347
c_p_usvet	.0038512	.0223375	0.17	0.863	-.0399296	.047632
c_p_medlim	-.0026099	.0153836	-0.17	0.865	-.0327613	.0275415
c_p_prob_sexual	.0165348	.0119404	1.38	0.166	-.006868	.0399375
c_p_prob_escape	-.0055964	.0113731	-0.49	0.623	-.0278872	.0166945
c_p_prob_mh	.0069297	.0136857	0.51	0.613	-.0198938	.0337531
c_p_prob_drugalc	-.0199765	.0161385	-1.24	0.216	-.0516074	.0116545
c_misAB	-.0103328	.0221864	-0.47	0.641	-.0538174	.0331517
c_had_tc	-.017079	.0140951	-1.21	0.226	-.0447048	.0105469
c_cust_gt3	-.0106667	.0160841	-0.66	0.507	-.0421911	.0208576
c_age	-.0035961	.0012356	-2.91	0.004	-.0060178	-.0011743
c_npriarr	-.000225	.0019696	-0.11	0.909	-.0040853	.0036353
c_maxsent	-.0000259	.000033	-0.79	0.432	-.0000905	.0000387
cp_hasPriorI	-.0098534	.0289015	-0.34	0.733	-.0664993	.0467925
cp_lifer	-.2208711	.1273365	-1.73	0.083	-.4704461	.0287039
cp_single	.0206544	.0283292	0.73	0.466	-.0348697	.0761786
cp_black	.0402545	.0284602	1.41	0.157	-.0155265	.0960355
cp_latino	.0531171	.0333004	1.60	0.111	-.0121504	.1183846
cp_urban	-.0538911	.0291644	-1.85	0.065	-.1110522	.00327
cp_18under_1arr	.0091619	.0267407	0.34	0.732	-.0432489	.0615728
cp_p_iq	-.0004881	.0008992	-0.54	0.587	-.0022505	.0012743
cp_p_hsgrad	-.0128244	.0255731	-0.50	0.616	-.0629467	.0372979
cp_p_had_job	-.0358434	.0222469	-1.61	0.107	-.0794465	.0077597
cp_p_usvet	.0302292	.0493238	0.61	0.540	-.0664436	.1269021
cp_p_medlim	-.029654	.0278505	-1.06	0.287	-.0842401	.0249321
cp_p_prob_sexual	.0190809	.0232185	0.82	0.411	-.0264265	.0645882
cp_p_prob_escape	.004792	.0201438	0.24	0.812	-.0346892	.0442733
cp_p_prob_mh	.0020296	.0244413	0.08	0.934	-.0458745	.0499338
cp_p_prob_drugalc	-.0045655	.0443167	-0.10	0.918	-.0914246	.0822936
cp_misAB	.0097265	.0231888	0.42	0.675	-.0357228	.0551758
cp_had_tc	-.0666632	.022185	-3.00	0.003	-.110145	-.0231815
cp_cust_gt3	.0263548	.0291694	0.90	0.366	-.0308161	.0835258
cp_age	-.000057	.0015721	-0.04	0.971	-.0031383	.0030243
cp_npriarr	.0015449	.0021404	0.72	0.470	-.0026501	.00574
cp_maxsent	.0000876	.0000655	1.34	0.181	-.0000407	.0002159
r_rel_q2	.0156749	.0196877	0.80	0.426	-.0229122	.054262
r_rel_q3	.0485681	.0231294	2.10	0.036	.0032353	.093901
r_rel_q4	.0084762	.0237476	0.36	0.721	-.0380683	.0550206
r_rel_q5	.0419933	.0226081	1.86	0.063	-.0023177	.0863043
r_rel_q6	.0397426	.0227177	1.75	0.080	-.0047833	.0842686
r_rel_q7	.0483581	.0198526	2.44	0.015	.0094477	.0872684
r_rel_q8	.0245969	.0210088	1.17	0.242	-.0165796	.0657734
tier_tt	.0057455	.0111014	0.52	0.605	-.0160128	.0275039
r_cell	-.0162248	.0144214	-1.13	0.261	-.0444901	.0120406
c_cell	-.0093632	.0160448	-0.58	0.560	-.0408104	.022084
stretches	-.0010596	.0062968	-0.17	0.866	-.013401	.0112818
r_time2rel	-3.35e-06	.0000266	-0.13	0.900	-.0000554	.0000487
pct_total_tt	-.0003647	.0004346	-0.84	0.401	-.0012166	.0004871
numCellies	.0003219	.0009181	0.35	0.726	-.0014776	.0021214
cellsqft_tt	.0002531	.0005643	0.45	0.654	-.0008529	.0013591
_Ifac_tt_52	.0138888	.0387531	0.36	0.720	-.0620659	.0898436
_Ifac_tt_54	-.0141929	.0436246	-0.33	0.745	-.0996955	.0713098
_Ifac_tt_55	.0382191	.0448567	0.85	0.394	-.0496985	.1261366
_Ifac_tt_56	-.0297108	.0527655	-0.56	0.573	-.1331292	.0737077
_Ifac_tt_57	-.0175661	.0518376	-0.34	0.735	-.1191658	.0840337
_Ifac_tt_58	.0510942	.053202	0.96	0.337	-.0531798	.1553681
_Ifac_tt_59	.0187391	.0400771	0.47	0.640	-.0598105	.0972887

_Ifac_tt_60	-.0057888	.0356912	-0.16	0.871	-.0757423	.0641648
_Ifac_tt_61	.0047008	.0459757	0.10	0.919	-.0854098	.0948115
_Ifac_tt_62	.0089459	.0427759	0.21	0.834	-.0748933	.0927852
_Ifac_tt_63	.0726991	.0384253	1.89	0.058	-.0026132	.1480114
_Ifac_tt_64	.0230818	.0348744	0.66	0.508	-.0452708	.0914343
_Ifac_tt_65	-.0388321	.0410089	-0.95	0.344	-.1192081	.0415439
_Ifac_tt_66	-.0629264	.0480018	-1.31	0.190	-.1570081	.0311554
_Ifac_tt_68	.0229245	.0363192	0.63	0.528	-.0482599	.0941089
_Ifac_tt_69	-.0107315	.0402645	-0.27	0.790	-.0896484	.0681855
_Ifac_tt_73	.0853725	.0442523	1.93	0.054	-.0013603	.1721054
_Ifac_tt_75	-.0318701	.0534022	-0.60	0.551	-.1365366	.0727964
_Ifac_tt_76	.0363058	.0461243	0.79	0.431	-.0540962	.1267078
_Ifac_tt_77	.0233959	.0457607	0.51	0.609	-.0662934	.1130853
_Ifac_tt_78	.0264906	.0375817	0.70	0.481	-.0471682	.1001494
_Ifac_tt_81	.0347242	.0690669	0.50	0.615	-.1006445	.1700928
k	.0786662	.052817	1.49	0.136	-.0248532	.1821857
_cons	.7343729	.1670797	4.40	0.000	.4069028	1.061843
Mills						
rho1-rho0	-.1877638	.0739755	-2.54	0.011	-.3327532	-.0427744
ATE						
E(Y1-Y0)@X	-.0682056	.0835648	-0.82	0.414	-.2319897	.0955784

Outcome = Reincarceration for Any Crime

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Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                    Number of obs      =     10116
Treatment Model: Probit                        Replications       =        50
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r_has_postI	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
Treated						
r_staytime	-.0001181	.0000521	-2.27	0.023	-.0002201	-.0000161
r_single	-.0046694	.0235329	-0.20	0.843	-.0507931	.0414543
r_black	.0450196	.0361342	1.25	0.213	-.0258021	.1158412
r_latino	-.0120359	.0389427	-0.31	0.757	-.0883621	.0642903
r_urban	-.0389149	.0221817	-1.75	0.079	-.0823903	.0045605
r_18under_1arr	.0302439	.026511	1.14	0.254	-.0217167	.0822045
r_p_iq	-.000897	.000746	-1.20	0.229	-.0023592	.0005652
r_p_hsgrad	.0012518	.0173427	0.07	0.942	-.0327393	.035243
r_p_had_job	-.04209	.0258325	-1.63	0.103	-.0927208	.0085408
r_p_usvet	.0416086	.0324619	1.28	0.200	-.0220155	.1052328
r_p_medlim	-.0174855	.0262272	-0.67	0.505	-.0688899	.033919
r_p_prob_sexual	-.0349602	.027717	-1.26	0.207	-.0892845	.0193641
r_p_prob_escape	.0611448	.0189798	3.22	0.001	.023945	.0983446
r_p_prob_mh	.0571928	.0220562	2.59	0.010	.0139634	.1004222
r_p_prob_drugalc	.045774	.0318638	1.44	0.151	-.0166778	.1082259
r_misAB	-.0095493	.0273447	-0.35	0.727	-.0631438	.0440452
r_had_tc	.296053	.0254077	11.65	0.000	.2462548	.3458511
r_cust_gt3	.014452	.02515	0.57	0.566	-.0348412	.0637451
r_age	-.0101084	.0010803	-9.36	0.000	-.0122256	-.0079911
r_npriarr	.0151001	.0020667	7.31	0.000	.0110495	.0191508
r_maxsent	.0024857	.0003458	7.19	0.000	.0018079	.0031634
c_lifer	.1388076	.1754024	0.79	0.429	-.2049748	.48259
c_single	.0188255	.0218361	0.86	0.389	-.0239726	.0616235
c_black	.0447763	.0315166	1.42	0.155	-.0169951	.1065477
c_latino	.0729173	.0346799	2.10	0.036	.004946	.1408886
c_urban	-.0261034	.027513	-0.95	0.343	-.080028	.0278212
c_18under_1arr	.0630832	.0205288	3.07	0.002	.0228474	.103319
c_p_iq	.0006883	.0007012	0.98	0.326	-.0006859	.0020625

c_p_hsgrad	.0053595	.0208623	0.26	0.797	-.0355298	.0462489
c_p_had_job	.0094025	.0169614	0.55	0.579	-.0238413	.0426463
c_p_usvet	-.0094144	.0383964	-0.25	0.806	-.08467	.0658412
c_p_medlim	-.0493544	.0173319	-2.85	0.004	-.0833243	-.0153844
c_p_prob_sexual	-.0143054	.0266703	-0.54	0.592	-.0665781	.0379674
c_p_prob_escape	.0069183	.0180464	0.38	0.701	-.028452	.0422886
c_p_prob_mh	.0039003	.0201074	0.19	0.846	-.0355095	.04331
c_p_prob_drugalc	.0247449	.0358468	0.69	0.490	-.0455135	.0950033
c_misAB	.0353848	.0293825	1.20	0.228	-.0222038	.0929734
c_had_tc	-.0210926	.0255358	-0.83	0.409	-.0711419	.0289568
c_cust_gt3	-.0029582	.0228669	-0.13	0.897	-.0477765	.0418601
c_age	.0031592	.0022374	1.41	0.158	-.001226	.0075445
c_npriarr	.0027918	.0020536	1.36	0.174	-.0012332	.0068167
c_maxsent	-.0001672	.0000898	-1.86	0.062	-.0003432	8.71e-06
cp_hasPriorI	.0513197	.0466794	1.10	0.272	-.0401702	.1428097
cp_lifer	-.1661085	.2548591	-0.65	0.515	-.6656232	.3334062
cp_single	.0713311	.0506372	1.41	0.159	-.0279159	.1705782
cp_black	-.0966783	.0494088	-1.96	0.050	-.1935177	.0001612
cp_latino	-.0659959	.0719968	-0.92	0.359	-.207107	.0751152
cp_urban	-.0127975	.0594378	-0.22	0.830	-.1292935	.1036986
cp_18under_1arr	.0084456	.0448926	0.19	0.851	-.0795423	.0964334
cp_p_iq	-.0031052	.0013744	-2.26	0.024	-.0057991	-.0004114
cp_p_hsgrad	-.0202908	.0429146	-0.47	0.636	-.1044019	.0638203
cp_p_had_job	-.0176641	.046064	-0.38	0.701	-.1079479	.0726197
cp_p_usvet	.0303845	.0792147	0.38	0.701	-.1248735	.1856425
cp_p_medlim	-.0497686	.043917	-1.13	0.257	-.1358444	.0363072
cp_p_prob_sexual	-.010801	.0564024	-0.19	0.848	-.1213477	.0997458
cp_p_prob_escape	-.0119222	.0373485	-0.32	0.750	-.0851239	.0612795
cp_p_prob_mh	.0192038	.0388256	0.49	0.621	-.056893	.0953007
cp_p_prob_drugalc	.0295702	.0654943	0.45	0.652	-.0987964	.1579367
cp_misAB	.0424862	.0397039	1.07	0.285	-.035332	.1203043
cp_had_tc	-.0858726	.047143	-1.82	0.069	-.1782711	.006526
cp_cust_gt3	-.0431424	.0392025	-1.10	0.271	-.1199779	.0336931
cp_age	-.0027952	.0025024	-1.12	0.264	-.0076998	.0021093
cp_npriarr	.0034666	.0044214	0.78	0.433	-.0051992	.0121324
cp_maxsent	.0000649	.0001458	0.44	0.656	-.000221	.0003507
r_rel_q2	.0263989	.0406282	0.65	0.516	-.0532309	.1060286
r_rel_q3	-.0222037	.0326961	-0.68	0.497	-.0862869	.0418795
r_rel_q4	-.070148	.0369017	-1.90	0.057	-.142474	.002178
r_rel_q5	-.0544748	.0357047	-1.53	0.127	-.1244547	.015505
r_rel_q6	-.0494885	.0406492	-1.22	0.223	-.1291596	.0301825
r_rel_q7	-.0016722	.0383639	-0.04	0.965	-.076864	.0735197
r_rel_q8	-.0492224	.0372531	-1.32	0.186	-.1222371	.0237923
tier_tt	.0023243	.0166147	0.14	0.889	-.0302399	.0348886
r_cell	-.0321787	.0231062	-1.39	0.164	-.0774661	.0131087
c_cell	-.0095008	.0193493	-0.49	0.623	-.0474247	.0284231
stretches	-.0139712	.0089444	-1.56	0.118	-.0315019	.0035596
r_time2rel	-.0000476	.0000429	-1.11	0.267	-.0001316	.0000364
pct_total_tt	.0007546	.0008136	0.93	0.354	-.0008401	.0023493
numCellies	-.001421	.0014705	-0.97	0.334	-.0043032	.0014611
cellsqft_tt	-.0004531	.0009262	-0.49	0.625	-.0022683	.0013622
_Ifac_tt_52	-.0506908	.0488927	-1.04	0.300	-.1465188	.0451371
_Ifac_tt_54	-.194695	.0635922	-3.06	0.002	-.3193335	-.0700565
_Ifac_tt_55	.0375472	.0501212	0.75	0.454	-.0606886	.1357831
_Ifac_tt_56	.005274	.0691752	0.08	0.939	-.130307	.140855
_Ifac_tt_57	-.1357658	.0584997	-2.32	0.020	-.250423	-.0211085
_Ifac_tt_58	-.0769915	.0697522	-1.10	0.270	-.2137033	.0597202
_Ifac_tt_59	-.0364962	.0478708	-0.76	0.446	-.1303211	.0573288
_Ifac_tt_60	-.101115	.053324	-1.90	0.058	-.205628	.0033981
_Ifac_tt_61	-.0203778	.0737381	-0.28	0.782	-.1649018	.1241461
_Ifac_tt_62	-.0166019	.0753616	-0.22	0.826	-.164308	.1311042
_Ifac_tt_63	-.0443647	.0654612	-0.68	0.498	-.1726663	.0839368
_Ifac_tt_64	-.0120814	.0468306	-0.26	0.796	-.1038676	.0797048
_Ifac_tt_65	.0898225	.0564166	1.59	0.111	-.020752	.200397
_Ifac_tt_66	.0084475	.0780151	0.11	0.914	-.1444592	.1613542
_Ifac_tt_68	-.1027032	.0497487	-2.06	0.039	-.2002089	-.0051975
_Ifac_tt_69	-.0135194	.0733886	-0.18	0.854	-.1573584	.1303196
_Ifac_tt_73	-.025841	.0648214	-0.40	0.690	-.1528885	.1012065
_Ifac_tt_75	-.091484	.0648679	-1.41	0.158	-.2186227	.0356546
_Ifac_tt_76	-.0018232	.0528763	-0.03	0.972	-.1054588	.1018124

_Ifac_tt_77	-.0366883	.0527401	-0.70	0.487	-.1400571	.0666805
_Ifac_tt_78	-.0132825	.0508545	-0.26	0.794	-.1129556	.0863905
_Ifac_tt_81	-.2117961	.0922404	-2.30	0.022	-.392584	-.0310082
k	-.098289	.0591513	-1.66	0.097	-.2142234	.0176453
_cons	.7607978	.3090697	2.46	0.014	.1550323	1.366563
Untreated						
r_staytime	-.0001611	.0000255	-6.33	0.000	-.000211	-.0001112
r_single	-.002366	.0122091	-0.19	0.846	-.0262953	.0215633
r_black	.0218457	.0225502	0.97	0.333	-.0223519	.0660432
r_latino	-.0165217	.029827	-0.55	0.580	-.0749816	.0419381
r_urban	-.0149925	.0152093	-0.99	0.324	-.0448021	.0148171
r_18under_1arr	.0302254	.0139023	2.17	0.030	.0029775	.0574734
r_p_iq	.000578	.0005084	1.14	0.256	-.0004184	.0015744
r_p_hsgrad	-.0556977	.0111886	-4.98	0.000	-.077627	-.0337683
r_p_had_job	-.0807885	.01632	-4.95	0.000	-.1127751	-.048802
r_p_usvet	-.0313815	.0219108	-1.43	0.152	-.0743258	.0115629
r_p_medlim	-.0214754	.0135852	-1.58	0.114	-.0481019	.0051512
r_p_prob_sexual	.0598167	.0144596	4.14	0.000	.0314764	.088157
r_p_prob_escape	.039771	.0116456	3.42	0.001	.0169461	.062596
r_p_prob_mh	.0586177	.0121902	4.81	0.000	.0347252	.0825101
r_p_prob_drugalc	.0548678	.0210518	2.61	0.009	.013607	.0961285
r_misAB	.0076549	.017202	0.45	0.656	-.0260603	.0413702
r_had_tc	.2701568	.0137569	19.64	0.000	.2431937	.2971198
r_cust_gt3	.0544498	.0171016	3.18	0.001	.0209313	.0879683
r_age	-.0086817	.0007274	-11.94	0.000	-.0101073	-.0072561
r_npriarr	.0167991	.0015727	10.68	0.000	.0137166	.0198815
r_maxsent	.0023312	.0002008	11.61	0.000	.0019376	.0027248
c_lifer	.0037925	.0559249	0.07	0.946	-.1058182	.1134033
c_single	-.0015038	.0128541	-0.12	0.907	-.0266973	.0236896
c_black	.0138917	.015238	0.91	0.362	-.0159743	.0437576
c_latino	.0161084	.0227757	0.71	0.479	-.028531	.0607479
c_urban	-.0063522	.0160245	-0.40	0.692	-.0377596	.0250552
c_18under_1arr	-.0120785	.0125489	-0.96	0.336	-.0366739	.012517
c_p_iq	-.0001306	.0004239	-0.31	0.758	-.0009614	.0007002
c_p_hsgrad	.009951	.0143887	0.69	0.489	-.0182504	.0381523
c_p_had_job	.0070184	.0100601	0.70	0.485	-.012699	.0267358
c_p_usvet	.0019604	.0264168	0.07	0.941	-.0498156	.0537365
c_p_medlim	.0199553	.0140953	1.42	0.157	-.007671	.0475816
c_p_prob_sexual	-.0062227	.0144715	-0.43	0.667	-.0345864	.0221411
c_p_prob_escape	-.004591	.0116207	-0.40	0.693	-.027367	.0181851
c_p_prob_mh	-.0096221	.0119639	-0.80	0.421	-.033071	.0138268
c_p_prob_drugalc	-.0244811	.0201625	-1.21	0.225	-.0639989	.0150367
c_misAB	-.0082297	.0208178	-0.40	0.693	-.0490318	.0325724
c_had_tc	-.0420552	.014338	-2.93	0.003	-.0701572	-.0139532
c_cust_gt3	-.0263115	.0147677	-1.78	0.075	-.0552556	.0026327
c_age	-.0046384	.0011634	-3.99	0.000	-.0069186	-.0023583
c_npriarr	-.0006814	.0024037	-0.28	0.777	-.0053925	.0040297
c_maxsent	.0000115	.0000333	0.35	0.730	-.0000538	.0000768
cp_hasPriorI	.0076246	.0256943	0.30	0.767	-.0427353	.0579845
cp_lifer	-.3912991	.1533888	-2.55	0.011	-.6919356	-.0906626
cp_single	.0827124	.032173	2.57	0.010	.0196545	.1457702
cp_black	.0249131	.0275341	0.90	0.366	-.0290527	.0788789
cp_latino	.0075314	.0441559	0.17	0.865	-.0790125	.0940754
cp_urban	-.0525658	.0311084	-1.69	0.091	-.1135372	.0084055
cp_18under_1arr	.032697	.0248641	1.32	0.189	-.0160357	.0814297
cp_p_iq	-.0011645	.0008062	-1.44	0.149	-.0027445	.0004155
cp_p_hsgrad	-.0137362	.0259695	-0.53	0.597	-.0646354	.037163
cp_p_had_job	-.0228505	.0244523	-0.93	0.350	-.0707761	.0250752
cp_p_usvet	.0833698	.0452717	1.84	0.066	-.0053612	.1721007
cp_p_medlim	-.0215143	.0218851	-0.98	0.326	-.0644083	.0213797
cp_p_prob_sexual	.0422905	.0311759	1.36	0.175	-.0188131	.1033941
cp_p_prob_escape	.0044821	.0186725	0.24	0.810	-.0321152	.0410794
cp_p_prob_mh	.0055265	.0223798	0.25	0.805	-.0383372	.0493902
cp_p_prob_drugalc	.0159267	.043231	0.37	0.713	-.0688045	.100658
cp_misAB	-.0013934	.0319876	-0.04	0.965	-.064088	.0613012
cp_had_tc	-.0862428	.0299862	-2.88	0.004	-.1450148	-.0274708
cp_cust_gt3	.021832	.0249058	0.88	0.381	-.0269825	.0706465
cp_age	-.0011428	.0012477	-0.92	0.360	-.0035883	.0013028
cp_npriarr	.0015075	.0022983	0.66	0.512	-.002997	.0060121

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     cp_maxsent |   .0002035   .0000719     2.83   0.005     .0000625    .0003445
       r_rel_q2 |   .0111962   .0215607     0.52   0.604    -.031062    .0534543
       r_rel_q3 |  -.0252922    .021479    -1.18   0.239    -.0673902    .0168059
       r_rel_q4 |  -.0537895    .023733    -2.27   0.023    -.1003052   -.0072737
       r_rel_q5 |   -.013808   .0265881    -0.52   0.604    -.0659198    .0383038
       r_rel_q6 |  -.0341199   .0221291    -1.54   0.123    -.0774921    .0092524
       r_rel_q7 |  -.0388392   .0190023    -2.04   0.041    -.0760831   -.0015954
       r_rel_q8 |  -.0523449   .0195034    -2.68   0.007    -.0905709   -.0141188
        tier_tt |   .0076951    .012082     0.64   0.524    -.0159852    .0313754
         r_cell |   .0289268   .0121436     2.38   0.017     .0051258    .0527279
         c_cell |   .0071728   .0132614     0.54   0.589    -.018819    .0331646
      stretches |   -.001237   .0053523    -0.23   0.817    -.0117274    .0092534
     r_time2rel |  -.0000441    .000021    -2.10   0.036    -.0000853   -2.85e-06
   pct_total_tt |   -.000565   .0003633    -1.56   0.120    -.0012771    .0001471
     numCellies |  -.0011589   .0008898    -1.30   0.193    -.002903    .0005851
    cellsqft_tt |  -.0000434   .0006062    -0.07   0.943    -.0012315    .0011447
    _Ifac_tt_52 |  -.0216526   .0342487    -0.63   0.527    -.0887788    .0454736
    _Ifac_tt_54 |   -.051452   .0442705    -1.16   0.245    -.1382206    .0353165
    _Ifac_tt_55 |   .0420683   .0373888     1.13   0.261    -.0312124     .115349
    _Ifac_tt_56 |  -.0572032   .0522602    -1.09   0.274    -.1596313    .0452249
    _Ifac_tt_57 |  -.0463332   .0453351    -1.02   0.307    -.1351884    .0425219
    _Ifac_tt_58 |    .005493   .0529959     0.10   0.917    -.0983771    .1093631
    _Ifac_tt_59 |   .0512905   .0381499     1.34   0.179    -.0234819    .1260629
    _Ifac_tt_60 |   .0142244   .0365882     0.39   0.697    -.0574872     .085936
    _Ifac_tt_61 |  -.0252735   .0507308    -0.50   0.618    -.124704    .0741571
    _Ifac_tt_62 |   .0134187   .0523713     0.26   0.798    -.0892271    .1160645
    _Ifac_tt_63 |    .016741   .0470714     0.36   0.722    -.0755172    .1089992
    _Ifac_tt_64 |   .0177791    .031571     0.56   0.573    -.044099    .0796572
    _Ifac_tt_65 |  -.0692635   .0468992    -1.48   0.140    -.1611842    .0226572
    _Ifac_tt_66 |  -.0268825   .0435134    -0.62   0.537    -.1121672    .0584021
    _Ifac_tt_68 |   .0313213   .0398161     0.79   0.431    -.0467169    .1093594
    _Ifac_tt_69 |  -.0661609   .0445036    -1.49   0.137    -.1533865    .0210646
    _Ifac_tt_73 |   .0530061   .0383179     1.38   0.167    -.0220956    .1281078
    _Ifac_tt_75 |  -.1069644   .0407465    -2.63   0.009    -.1868261   -.0271027
    _Ifac_tt_76 |  -.0098332   .0475784    -0.21   0.836    -.1030852    .0834187
    _Ifac_tt_77 |   .0075689   .0406041     0.19   0.852    -.0720137    .0871516
    _Ifac_tt_78 |   .0158991    .033604     0.47   0.636    -.0499636    .0817617
    _Ifac_tt_81 |    .066377   .0770526     0.86   0.389    -.0846433    .2173974
              k |   .0916278   .0524263     1.75   0.081    -.0111259    .1943815
          _cons |   .7474053   .1562626     4.78   0.000     .4411363    1.053674
----------------+----------------------------------------------------------------
Mills           |
      rho1-rho0 |  -.1899169   .0787764    -2.41   0.016    -.3443158   -.0355179
----------------+----------------------------------------------------------------
ATE             |
     E(Y1-Y0)@X |  -.0665025   .0780754    -0.85   0.394    -.2195275    .0865225
---------------------------------------------------------------------------------
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Switching: Homicide

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Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                     Number of obs      =     10116
Treatment Model: Probit                         Replications       =        50
------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
   r_post_h22 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Treated      |
  r_staytime |   .0000253   .0000158     1.60   0.110    -5.69e-06    .0000563
    r_single |    .003313   .0060468     0.55   0.584    -.0085384    .0151645
     r_black |   .0008835   .0131755     0.07   0.947      -.02494     .026707
    r_latino |  -.0067205   .0168667    -0.40   0.690    -.0397787    .0263376
     r_urban |    .011357   .0065732     1.73   0.084    -.0015262    .0242401
r_18under_~r |   .0214436   .0077028     2.78   0.005     .0063464    .0365407
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r_p_iq	.0000522	.0003049	0.17	0.864	-.0005453	.0006498
r_p_hsgrad	-.0032116	.0088094	-0.36	0.715	-.0204777	.0140545
r_p_had_job	.0226104	.0118423	1.91	0.056	-.0006	.0458209
r_p_usvet	.0071907	.0083338	0.86	0.388	-.0091433	.0235247
r_p_medlim	-.0086343	.0093676	-0.92	0.357	-.0269945	.0097259
r_p_prob_s~l	-.008549	.0131224	-0.65	0.515	-.0342684	.0171704
r_p_prob_e~e	.0133016	.0069409	1.92	0.055	-.0003024	.0269056
r_p_prob_mh	-.0021419	.0078594	-0.27	0.785	-.0175461	.0132622
r_p_prob_d~c	.0063719	.0098794	0.64	0.519	-.0129913	.0257351
r_misAB	.0130006	.0123053	1.06	0.291	-.0111173	.0371185
r_had_tc	-.0049668	.0109287	-0.45	0.649	-.0263867	.0164531
r_cust_gt3	.0157912	.0123271	1.28	0.200	-.0083695	.0399519
r_age	-.0009233	.0003485	-2.65	0.008	-.0016063	-.0002403
r_npriarr	.0010009	.0007612	1.31	0.189	-.000491	.0024928
r_maxsent	-.0001027	.0001315	-0.78	0.435	-.0003604	.000155
c_lifer	.0214575	.0229345	0.94	0.349	-.0234932	.0664083
c_single	-.0067466	.0086612	-0.78	0.436	-.0237222	.0102289
c_black	.003983	.0110673	0.36	0.719	-.0177086	.0256745
c_latino	.0029823	.0192203	0.16	0.877	-.0346889	.0406534
c_urban	.0151939	.0071071	2.14	0.033	.0012641	.0291236
c_18under_~r	.0099513	.0097777	1.02	0.309	-.0092127	.0291154
c_p_iq	-.0001795	.0002711	-0.66	0.508	-.0007107	.0003518
c_p_hsgrad	.0119275	.0066528	1.79	0.073	-.0011118	.0249668
c_p_had_job	.0129411	.007827	1.65	0.098	-.0023997	.0282818
c_p_usvet	-.0016895	.0133945	-0.13	0.900	-.0279421	.0245632
c_p_medlim	.0016996	.0092448	0.18	0.854	-.0164198	.019819
c_p_prob_s~l	-.0227265	.0134482	-1.69	0.091	-.0490845	.0036315
c_p_prob_e~e	.004055	.0078634	0.52	0.606	-.0113569	.0194669
c_p_prob_mh	.0126508	.0084767	1.49	0.136	-.0039631	.0292648
c_p_prob_d~c	-.0186185	.0142424	-1.31	0.191	-.0465331	.0092961
c_misAB	.0048059	.0081352	0.59	0.555	-.0111388	.0207507
c_had_tc	-.0132698	.0092334	-1.44	0.151	-.031367	.0048274
c_cust_gt3	.002602	.0111658	0.23	0.816	-.0192826	.0244865
c_age	-.000181	.0004398	-0.41	0.681	-.0010431	.000681
c_npriarr	-.0011157	.0006695	-1.67	0.096	-.0024279	.0001966
c_maxsent	.0000146	.0000157	0.93	0.354	-.0000162	.0000454
cp_pri_h32	-.018295	.014107	-1.30	0.195	-.0459441	.0093542
cp_hasPriorI	.0088146	.0186703	0.47	0.637	-.0277785	.0454077
cp_lifer	.1096087	.0579109	1.89	0.058	-.0038945	.2231119
cp_single	.0062453	.017505	0.36	0.721	-.0280638	.0405545
cp_black	.0182087	.0201006	0.91	0.365	-.0211878	.0576052
cp_latino	.0015374	.0249333	0.06	0.951	-.047331	.0504058
cp_urban	.0026901	.020654	0.13	0.896	-.037791	.0431713
cp_18under~r	-.0112129	.0165277	-0.68	0.497	-.0436065	.0211807
cp_p_iq	-.0001237	.0005517	-0.22	0.823	-.0012051	.0009577
cp_p_hsgrad	-.0165673	.0184679	-0.90	0.370	-.0527636	.0196291
cp_p_had_job	.0102303	.0174232	0.59	0.557	-.0239185	.044379
cp_p_usvet	-.0048468	.0174647	-0.28	0.781	-.0390769	.0293834
cp_p_medlim	-.0044499	.012275	-0.36	0.717	-.0285085	.0196087
cp_p_prob~al	-.0257684	.0191131	-1.35	0.178	-.0632294	.0116925
cp_p_prob~pe	-.0242831	.0131634	-1.84	0.065	-.0500829	.0015167
cp_p_prob_mh	.0162441	.0170577	0.95	0.341	-.0171884	.0496767
cp_p_prob_~c	-.0298064	.0268257	-1.11	0.267	-.0823837	.022771
cp_misAB	.0070014	.0190632	0.37	0.713	-.0303618	.0443646
cp_had_tc	.0115232	.0193637	0.60	0.552	-.026429	.0494754
cp_cust_gt3	.0048091	.015679	0.31	0.759	-.0259212	.0355395
cp_age	-.0005089	.0009011	-0.56	0.572	-.002275	.0012572
cp_npriarr	-.0004676	.0017467	-0.27	0.789	-.0038911	.0029559
cp_maxsent	-.000078	.0000307	-2.54	0.011	-.0001382	-.0000179
r_rel_q2	.0280055	.0123375	2.27	0.023	.0038245	.0521866
r_rel_q3	.0175205	.0171362	1.02	0.307	-.0160659	.0511069
r_rel_q4	.0058983	.0135568	0.44	0.664	-.0206725	.0324692
r_rel_q5	.0120226	.0173516	0.69	0.488	-.0219859	.046031
r_rel_q6	.0315572	.018376	1.72	0.086	-.004459	.0675735
r_rel_q7	.0168298	.0153609	1.10	0.273	-.013277	.0469366
r_rel_q8	.0254044	.017837	1.42	0.154	-.0095555	.0603644
tier_tt	-.0042239	.0070844	-0.60	0.551	-.0181091	.0096613
r_cell	.0116209	.0095068	1.22	0.222	-.007012	.0302539
c_cell	.0103877	.0072145	1.44	0.150	-.0037524	.0245278
stretches	-.0077691	.0032258	-2.41	0.016	-.0140915	-.0014467

r_time2rel	2.29e-06	.0000144	0.16	0.873	-.0000258	.0000304
pct_total_tt	.0001697	.0002176	0.78	0.435	-.0002567	.0005961
numCellies	-.0004838	.0008016	-0.60	0.546	-.0020549	.0010873
cellsqft_tt	.0004415	.000322	1.37	0.170	-.0001896	.0010727
_Ifac_tt_52	-.0038901	.020175	-0.19	0.847	-.0434324	.0356523
_Ifac_tt_54	.0131383	.0242836	0.54	0.588	-.0344567	.0607333
_Ifac_tt_55	.0054114	.0227593	0.24	0.812	-.0391961	.0500189
_Ifac_tt_56	-.0367887	.019493	-1.89	0.059	-.0749943	.001417
_Ifac_tt_57	.0223558	.0207698	1.08	0.282	-.0183522	.0630639
_Ifac_tt_58	.0314612	.0364604	0.86	0.388	-.0399999	.1029223
_Ifac_tt_59	-.0162454	.0162596	-1.00	0.318	-.0481136	.0156229
_Ifac_tt_60	.0195599	.0252222	0.78	0.438	-.0298747	.0689946
_Ifac_tt_61	.0220013	.034236	0.64	0.520	-.0451	.0891026
_Ifac_tt_62	.0249404	.0381523	0.65	0.513	-.0498369	.0997176
_Ifac_tt_63	.0805449	.0494933	1.63	0.104	-.0164603	.17755
_Ifac_tt_64	-.0204165	.0175383	-1.16	0.244	-.0547909	.0139579
_Ifac_tt_65	.0124847	.0239737	0.52	0.603	-.0345029	.0594723
_Ifac_tt_66	-.0043915	.0225521	-0.19	0.846	-.0485928	.0398099
_Ifac_tt_68	-.0165311	.017769	-0.93	0.352	-.0513578	.0182955
_Ifac_tt_69	.0398307	.0340662	1.17	0.242	-.0269378	.1065991
_Ifac_tt_73	.0177316	.0357184	0.50	0.620	-.0522751	.0877383
_Ifac_tt_75	.0304902	.0230797	1.32	0.186	-.0147452	.0757256
_Ifac_tt_76	.0242269	.0286981	0.84	0.399	-.0320203	.0804742
_Ifac_tt_77	.0026661	.0247878	0.11	0.914	-.045917	.052493
_Ifac_tt_78	.0180936	.0245108	0.74	0.460	-.0299466	.0661338
_Ifac_tt_81	-.0031817	.0357857	-0.09	0.929	-.0733203	.066957
k	-.0437573	.0206698	-2.12	0.034	-.0842692	-.0032453
_cons	-.0446069	.0942221	-0.47	0.636	-.2292789	.140065
Untreated						
r_staytime	-.0000123	7.67e-06	-1.61	0.108	-.0000274	2.72e-06
r_single	-.0074288	.0042295	-1.76	0.079	-.0157184	.0008608
r_black	.0023139	.0043402	0.53	0.594	-.0061927	.0108206
r_latino	-.0068663	.0050483	-1.36	0.174	-.0167607	.0030282
r_urban	.0057888	.002949	1.96	0.050	8.77e-06	.0115688
r_18under_~r	.0162496	.0036088	4.50	0.000	.0091765	.0233227
r_p_iq	.0000194	.000116	0.17	0.867	-.000208	.0002468
r_p_hsgrad	-.0034657	.0027115	-1.28	0.201	-.00878	.0018487
r_p_had_job	.015261	.0050361	3.03	0.002	.0053905	.0251314
r_p_usvet	.0016691	.0028384	0.59	0.557	-.003894	.0072321
r_p_medlim	.0022852	.0034431	0.66	0.507	-.0044632	.0090337
r_p_prob_s~l	-.0038202	.0042893	-0.89	0.373	-.012227	.0045866
r_p_prob_e~e	-.0002156	.0023621	-0.09	0.927	-.0048452	.004414
r_p_prob_mh	-.0033166	.0031785	-1.04	0.297	-.0095464	.0029133
r_p_prob_d~c	.0055137	.0038567	1.43	0.153	-.0020452	.0130726
r_misAB	-.0010417	.0047619	-0.22	0.827	-.0103749	.0082916
r_had_tc	-.0051749	.0035418	-1.46	0.144	-.0121167	.001767
r_cust_gt3	.0057473	.0040315	1.43	0.154	-.0021544	.0136489
r_age	-.0007693	.0001321	-5.82	0.000	-.0010283	-.0005104
r_npriarr	.0005353	.0003204	1.67	0.095	-.0000927	.0011633
r_maxsent	-3.64e-06	.0000536	-0.07	0.946	-.0001087	.0001014
c_lifer	-.0139738	.0158872	-0.88	0.379	-.0451122	.0171645
c_single	.0002566	.0030832	0.08	0.934	-.0057863	.0062996
c_black	.0027366	.0037243	0.73	0.462	-.0045629	.0100361
c_latino	.0071196	.0046254	1.54	0.124	-.0019461	.0161853
c_urban	-.0047768	.0037948	-1.26	0.208	-.0122145	.0026609
c_18under_~r	.0097509	.0042642	2.29	0.022	.0013933	.0181085
c_p_iq	.0000715	.0001184	0.60	0.546	-.0001605	.0003035
c_p_hsgrad	-.007449	.0034548	-2.16	0.031	-.0142204	-.0006777
c_p_had_job	-.0024222	.0033323	-0.73	0.467	-.0089535	.004109
c_p_usvet	.0044067	.0052221	0.84	0.399	-.0058284	.0146418
c_p_medlim	-.0027254	.0029177	-0.93	0.350	-.008444	.0029931
c_p_prob_s~l	-.0034783	.0050322	-0.69	0.489	-.0133413	.0063846
c_p_prob_e~e	.0019426	.0035328	0.55	0.582	-.0049816	.0088667
c_p_prob_mh	-.0010579	.0026177	-0.40	0.686	-.0061885	.0040727
c_p_prob_d~c	-.0027836	.0048459	-0.57	0.566	-.0122814	.0067142
c_misAB	.0024851	.0035697	0.70	0.486	-.0045113	.0094815
c_had_tc	.0003504	.0040612	0.09	0.931	-.0076094	.0083102
c_cust_gt3	-.0054602	.0039247	-1.39	0.164	-.0131524	.002232
c_age	.0002964	.0001761	1.68	0.092	-.0000486	.0006415

c_npriarr	-3.41e-06	.0002379	-0.01	0.989	-.0004698	.0004629
c_maxsent	-.0000203	.0000147	-1.38	0.167	-.000049	8.48e-06
cp_pri_h32	.0038407	.0058316	0.66	0.510	-.007589	.0152704
cp_hasPriorI	-.0007542	.0083172	-0.09	0.928	-.0170556	.0155472
cp_lifer	-.0427483	.0410377	-1.04	0.298	-.1231808	.0376841
cp_single	-.0092654	.0081362	-1.14	0.255	-.025212	.0066812
cp_black	.00373	.0063169	0.59	0.555	-.0086509	.0161109
cp_latino	.0002591	.0094465	0.03	0.978	-.0182557	.0187738
cp_urban	.0017381	.0065635	0.26	0.791	-.0111261	.0146024
cp_18under~r	.0102509	.007147	1.43	0.151	-.0037569	.0242587
cp_p_iq	-.0004256	.0002256	-1.89	0.059	-.0008678	.0000167
cp_p_hsgrad	.000254	.0072517	0.04	0.972	-.0139591	.014467
cp_p_had_job	-.0065584	.0062277	-1.05	0.292	-.0187645	.0056478
cp_p_usvet	-.0080118	.0073804	-1.09	0.278	-.0224772	.0064536
cp_p_medlim	-.0144558	.0071086	-2.03	0.042	-.0283885	-.0005231
cp_p_prob~al	-.0053827	.0074346	-0.72	0.469	-.0199543	.0091889
cp_p_prob~pe	.00512	.0056644	0.90	0.366	-.0059821	.0162222
cp_p_prob_mh	-.0020505	.0059074	-0.35	0.729	-.0136287	.0095278
cp_p_prob_~c	-.0242605	.0130442	-1.86	0.063	-.0498266	.0013056
cp_misAB	.0101548	.0081442	1.25	0.212	-.0058075	.0261172
cp_had_tc	-.0037997	.0061123	-0.62	0.534	-.0157796	.0081802
cp_cust_gt3	.0034491	.0078927	0.44	0.662	-.0120203	.0189185
cp_age	.0005803	.0003853	1.51	0.132	-.0001748	.0013354
cp_npriarr	-.0010202	.0004559	-2.24	0.025	-.0019138	-.0001266
cp_maxsent	.0000212	.0000173	1.23	0.218	-.0000126	.0000551
r_rel_q2	-.0148213	.0053037	-2.79	0.005	-.0252164	-.0044262
r_rel_q3	-.0107775	.005376	-2.00	0.045	-.0213142	-.0002407
r_rel_q4	-.0055101	.0067068	-0.82	0.411	-.0186552	.007635
r_rel_q5	-.0106217	.0065479	-1.62	0.105	-.0234554	.002
r_rel_q6	-.0075636	.0057091	-1.32	0.185	-.0187532	.003626
r_rel_q7	-.0068123	.006434	-1.06	0.290	-.0194228	.0057981
r_rel_q8	-.0159946	.0052095	-3.07	0.002	-.0262051	-.0057842
tier_tt	.0061759	.0031336	1.97	0.049	.0000341	.0123177
r_cell	.0031488	.0036594	0.86	0.390	-.0040235	.0103211
c_cell	.0016956	.0041188	0.41	0.681	-.006377	.0097683
stretches	.0020173	.0018454	1.09	0.274	-.0015997	.0056343
r_time2rel	.0000145	6.88e-06	2.11	0.035	1.04e-06	.000028
pct_total_tt	6.07e-06	.0001116	0.05	0.957	-.0002126	.0002248
numCellies	.0003476	.0002747	1.27	0.206	-.0001908	.000886
cellsqft_tt	.0001702	.0001783	0.95	0.340	-.0001793	.0005197
_Ifac_tt_52	.0040383	.00593	0.68	0.496	-.0075842	.0156608
_Ifac_tt_54	.0068146	.0074204	0.92	0.358	-.0077291	.0213584
_Ifac_tt_55	.0190932	.009566	2.00	0.046	.0003442	.0378422
_Ifac_tt_56	.0005113	.0078263	0.07	0.948	-.014828	.0158505
_Ifac_tt_57	.0110726	.0080813	1.37	0.171	-.0047665	.0269116
_Ifac_tt_58	.0144811	.0134444	1.08	0.281	-.0118694	.0408316
_Ifac_tt_59	-.0072363	.0061274	-1.18	0.238	-.0192458	.0047731
_Ifac_tt_60	.0189195	.0113881	1.66	0.097	-.0034009	.0412398
_Ifac_tt_61	.0107058	.0139812	0.77	0.444	-.0166968	.0381083
_Ifac_tt_62	.0141239	.0108257	1.30	0.192	-.0070941	.0353419
_Ifac_tt_63	.007509	.0136007	0.55	0.581	-.0191478	.0341658
_Ifac_tt_64	.0145019	.0085131	1.70	0.088	-.0021834	.0311872
_Ifac_tt_65	.0467535	.0186869	2.50	0.012	.010128	.0833791
_Ifac_tt_66	.0030214	.0075271	0.40	0.688	-.0117314	.0177741
_Ifac_tt_68	.0134053	.0093039	1.44	0.150	-.00483	.0316406
_Ifac_tt_69	.0149931	.0083096	1.80	0.071	-.0012933	.0312796
_Ifac_tt_73	-.0142683	.0103531	-1.38	0.168	-.03456	.0060234
_Ifac_tt_75	.0073058	.0103521	0.71	0.480	-.012984	.0275956
_Ifac_tt_76	.010425	.0088754	1.17	0.240	-.0069704	.0278205
_Ifac_tt_77	.0178255	.0141454	1.26	0.208	-.0098991	.0455501
_Ifac_tt_78	.0085708	.0087414	0.98	0.327	-.0085621	.0257037
_Ifac_tt_81	.0353631	.0234166	1.51	0.131	-.0105326	.0812587
k	.0124565	.0186756	0.67	0.505	-.024147	.04906
_cons	.0386247	.037608	1.03	0.304	-.0350855	.112335
Mills						
rho1-rho0	-.0562138	.0309632	-1.82	0.069	-.1169005	.0044729
ATE						
E(Y1-Y0)@X	-.0589195	.029766	-1.98	0.048	-.1172598	-.0005791

Switching: Robbery

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Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                     Number of obs      =     10116
Treatment Model: Probit                         Replications       =        50
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r_post_h32	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
Treated						
r_staytime	1.84e-06	.0000162	0.11	0.910	-.00003	.0000337
r_single	.0071172	.0075933	0.94	0.349	-.0077655	.0219998
r_black	-.0058082	.0147781	-0.39	0.694	-.0347727	.0231562
r_latino	.0300893	.0199334	1.51	0.131	-.0089795	.0691581
r_urban	.0090685	.0086837	1.04	0.296	-.0079512	.0260881
r_18under_~r	.0194771	.0108464	1.80	0.073	-.0017815	.0407357
r_p_iq	-.000685	.0002985	-2.29	0.022	-.00127	-.0001
r_p_hsgrad	-.0124193	.008244	-1.51	0.132	-.0285772	.0037386
r_p_had_job	.0450982	.0113731	3.97	0.000	.0228073	.0673891
r_p_usvet	.0245154	.012838	1.91	0.056	-.0006466	.0496773
r_p_medlim	-.0019151	.0093741	-0.20	0.838	-.020288	.0164578
r_p_prob_s~l	-.0051203	.015714	-0.33	0.745	-.0359191	.0256785
r_p_prob_e~e	.0207065	.0076661	2.70	0.007	.0056812	.0357318
r_p_prob_mh	-.0031112	.0084739	-0.37	0.714	-.0197198	.0134974
r_p_prob_d~c	-.0344513	.0169623	-2.03	0.042	-.0676968	-.0012058
r_misAB	-.0030116	.0104927	-0.29	0.774	-.0235769	.0175538
r_had_tc	.0072842	.0118074	0.62	0.537	-.0158578	.0304261
r_cust_gt3	.013531	.0119462	1.13	0.257	-.0098831	.036945
r_age	-.002016	.0004251	-4.74	0.000	-.0028491	-.0011828
r_npriarr	.0042887	.0009238	4.64	0.000	.002478	.0060993
r_maxsent	-.0003202	.0001094	-2.93	0.003	-.0005347	-.0001057
c_lifer	-.075425	.046881	-1.61	0.108	-.16731	.0164599
c_single	.0131582	.0084136	1.56	0.118	-.0033322	.0296487
c_black	.0460656	.0208868	2.21	0.027	.0051282	.0870031
c_latino	.0014589	.0153615	0.09	0.924	-.0286491	.031567
c_urban	.0288655	.0162583	1.78	0.076	-.0030002	.0607313
c_18under_~r	.0249971	.0152641	1.64	0.101	-.00492	.0549142
c_p_iq	-.0006205	.0002258	-2.75	0.006	-.001063	-.000178
c_p_hsgrad	.002579	.0093386	0.28	0.782	-.0157244	.0208823
c_p_had_job	.0078845	.0094226	0.84	0.403	-.0105835	.0263524
c_p_usvet	.0147923	.0177368	0.83	0.404	-.0199712	.0495559
c_p_medlim	-.015154	.0067194	-2.26	0.024	-.0283238	-.0019843
c_p_prob_s~l	-.0177436	.0167516	-1.06	0.289	-.0505762	.0150889
c_p_prob_e~e	-.0027266	.0077831	-0.35	0.726	-.0179811	.012528
c_p_prob_mh	.008909	.0104267	0.85	0.393	-.0115269	.0293448
c_p_prob_d~c	-.0210856	.0194739	-1.08	0.279	-.0592538	.0170826
c_misAB	.0099984	.0110829	0.90	0.367	-.0117236	.0317205
c_had_tc	-.0068506	.0088488	-0.77	0.439	-.0241938	.0104927
c_cust_gt3	.0008045	.0098378	0.08	0.935	-.0184773	.0200863
c_age	-.0015018	.0007335	-2.05	0.041	-.0029395	-.0000642
c_npriarr	.0061773	.0020965	2.95	0.003	.0020683	.0102864
c_maxsent	.0000511	.0000258	1.98	0.047	5.69e-07	.0001017
cp_pri_h32	.0209568	.0167042	1.25	0.210	-.0117828	.0536963
cp_hasPriorI	.0292297	.0205811	1.42	0.156	-.0111085	.069568
cp_lifer	-.0605863	.0923076	-0.66	0.512	-.241506	.120333
cp_single	.0122042	.0192596	0.63	0.526	-.025544	.0499524
cp_black	.0050128	.0180964	0.28	0.782	-.0304555	.0404811
cp_latino	-.043042	.0280465	-1.53	0.125	-.0980123	.0119282
cp_urban	-.0024407	.0215362	-0.11	0.910	-.0446509	.0397696
cp_18under~r	.0054606	.0165139	0.33	0.741	-.0269062	.0378273
cp_p_iq	-.0002147	.0005413	-0.40	0.692	-.0012756	.0008461
cp_p_hsgrad	-.0193137	.0186493	-1.04	0.300	-.0558657	.0172382
cp_p_had_job	-.0164656	.0166663	-0.99	0.323	-.0491309	.0161998

cp_p_usvet	-.0350845	.0235673	-1.49	0.137	-.0812756	.0111065
cp_p_medlim	-.0121475	.0181334	-0.67	0.503	-.0476884	.0233933
cp_p_prob~al	.0150282	.0222721	0.67	0.500	-.0286242	.0586807
cp_p_prob~pe	.0189346	.0154803	1.22	0.221	-.0114063	.0492755
cp_p_prob_mh	.0014861	.0153851	0.10	0.923	-.0286681	.0316402
cp_p_prob_~c	-.0171991	.0317802	-0.54	0.588	-.0794872	.045089
cp_misAB	-.0140704	.0151924	-0.93	0.354	-.043847	.0157061
cp_had_tc	.0219012	.0173053	1.27	0.206	-.0120165	.0558188
cp_cust_gt3	.0108392	.0188738	0.57	0.566	-.0261528	.0478311
cp_age	.0002722	.000968	0.28	0.779	-.001625	.0021694
cp_npriarr	-.0022209	.0015068	-1.47	0.141	-.0051741	.0007324
cp_maxsent	.0000279	.0000543	0.51	0.607	-.0000786	.0001344
r_rel_q2	-.0133715	.0124059	-1.08	0.281	-.0376867	.0109437
r_rel_q3	-.0104284	.0147557	-0.71	0.480	-.0393489	.0184922
r_rel_q4	.0214019	.0174555	1.23	0.220	-.0128103	.0556141
r_rel_q5	.0124762	.0179202	0.70	0.486	-.0226468	.0475992
r_rel_q6	.0038421	.0163142	0.24	0.814	-.0281331	.0358172
r_rel_q7	-.0033912	.0143753	-0.24	0.814	-.0315663	.024784
r_rel_q8	.0043829	.0155094	0.28	0.777	-.0260149	.0347808
tier_tt	.0275614	.0077235	3.57	0.000	.0124237	.0426991
r_cell	.0006928	.0124449	0.06	0.956	-.0236987	.0250843
c_cell	-.0036946	.0108466	-0.34	0.733	-.0249535	.0175642
stretches	-.0012684	.0047165	-0.27	0.788	-.0105126	.0079757
r_time2rel	.0000186	.0000195	0.95	0.340	-.0000196	.0000568
pct_total_tt	-.0001148	.0003693	-0.31	0.756	-.0008385	.000609
numCellies	.0014618	.0008098	1.81	0.071	-.0001255	.003049
cellsqft_tt	-.0001621	.0006103	-0.27	0.790	-.0013583	.001034
_Ifac_tt_52	-.0372404	.023981	-1.55	0.120	-.0842422	.0097614
_Ifac_tt_54	.0028443	.0245334	0.12	0.908	-.0452403	.0509289
_Ifac_tt_55	.0002115	.0263666	0.01	0.994	-.0514661	.0518891
_Ifac_tt_56	.0283254	.0343071	0.83	0.409	-.0389151	.095566
_Ifac_tt_57	.0109426	.0367507	0.30	0.766	-.0610875	.0829727
_Ifac_tt_58	.0629314	.050013	1.26	0.208	-.0350922	.160955
_Ifac_tt_59	.0003678	.0229615	0.02	0.987	-.0446358	.0453715
_Ifac_tt_60	-.0124746	.0253005	-0.49	0.622	-.0620627	.0371135
_Ifac_tt_61	-.0016762	.0304962	-0.05	0.956	-.0614477	.0580953
_Ifac_tt_62	-.0174475	.0378028	-0.46	0.644	-.0915396	.0566447
_Ifac_tt_63	.0303605	.0413743	0.73	0.463	-.0507316	.1114526
_Ifac_tt_64	-.0209606	.0218706	-0.96	0.338	-.0638262	.0219049
_Ifac_tt_65	.0185614	.0346836	0.54	0.593	-.0494173	.0865401
_Ifac_tt_66	.0079167	.0211344	0.37	0.708	-.0335061	.0493394
_Ifac_tt_68	.0204492	.0241424	0.85	0.397	-.0268691	.0677675
_Ifac_tt_69	.0439166	.0450129	0.98	0.329	-.044307	.1321403
_Ifac_tt_73	.0092703	.0339152	0.27	0.785	-.0572023	.0757429
_Ifac_tt_75	-.0166335	.0303853	-0.55	0.584	-.0761875	.0429205
_Ifac_tt_76	-.0054203	.0347741	-0.16	0.876	-.0735763	.0627356
_Ifac_tt_77	-.0228488	.0343442	-0.67	0.506	-.0901621	.0444646
_Ifac_tt_78	.0005322	.0228963	0.02	0.981	-.0443437	.0454082
_Ifac_tt_81	.1055239	.0802755	1.31	0.189	-.0518131	.2628609
k	-.1590203	.0561278	-2.83	0.005	-.2690288	-.0490118
_cons	-.0021053	.1132287	-0.02	0.985	-.2240295	.2198189
Untreated						
r_staytime	-7.88e-06	.0000116	-0.68	0.498	-.0000307	.0000149
r_single	.0000358	.0044858	0.01	0.994	-.0087563	.0088279
r_black	.0190093	.0083033	2.29	0.022	.0027352	.0352834
r_latino	.0069097	.0104292	0.66	0.508	-.0135312	.0273507
r_urban	.0120654	.0048528	2.49	0.013	.0025539	.0215768
r_18under_~r	.0240778	.0058104	4.14	0.000	.0126896	.0354661
r_p_iq	.0001291	.0001724	0.75	0.454	-.0002089	.000467
r_p_hsgrad	-.001978	.0057051	-0.35	0.729	-.0131597	.0092038
r_p_had_job	.0386401	.0091932	4.20	0.000	.0206217	.0566584
r_p_usvet	.0046531	.0062084	0.75	0.454	-.0075151	.0168213
r_p_medlim	.0161384	.0062572	2.58	0.010	.0038745	.0284022
r_p_prob_s~l	-.0054491	.0064876	-0.84	0.401	-.0181645	.0072663
r_p_prob_e~e	.0074079	.005422	1.37	0.172	-.003219	.0180349
r_p_prob_mh	.0084343	.0060134	1.40	0.161	-.0033518	.0202205
r_p_prob_d~c	-.0097418	.0078776	-1.24	0.216	-.0251816	.0056981
r_misAB	-.0004668	.0081368	-0.06	0.954	-.0164147	.0154811
r_had_tc	.0110044	.0077214	1.43	0.154	-.0041293	.0261381

r_cust_gt3	.0168219	.0085211	1.97	0.048	.0001208	.033523
r_age	-.0011381	.0002753	-4.13	0.000	-.0016776	-.0005985
r_npriarr	.0031095	.0008054	3.86	0.000	.0015311	.004688
r_maxsent	-.0001698	.0000891	-1.91	0.057	-.0003443	4.84e-06
c_lifer	.0351875	.0241698	1.46	0.145	-.0121843	.0825594
c_single	-.0073932	.0052948	-1.40	0.163	-.0177707	.0029843
c_black	-.0019809	.009855	-0.20	0.841	-.0212964	.0173346
c_latino	-.0016973	.0080069	-0.21	0.832	-.0173906	.0139959
c_urban	.0004111	.0047892	0.09	0.932	-.0089755	.0097977
c_18under_~r	-.0008785	.0090672	-0.10	0.923	-.0186499	.0168929
c_p_iq	-.0001613	.0001686	-0.96	0.339	-.0004917	.000169
c_p_hsgrad	.0012691	.0051433	0.25	0.805	-.0088115	.0113498
c_p_had_job	-.0036099	.0048123	-0.75	0.453	-.0130418	.005822
c_p_usvet	.0019262	.0089001	0.22	0.829	-.0155178	.0193702
c_p_medlim	-.0069582	.0050422	-1.38	0.168	-.0168407	.0029243
c_p_prob_s~l	.003269	.0066986	0.49	0.626	-.00986	.0163981
c_p_prob_e~e	.001745	.0048252	0.36	0.718	-.0077122	.0112023
c_p_prob_mh	.0006136	.0052473	0.12	0.907	-.009671	.0108981
c_p_prob_d~c	.0057486	.0071347	0.81	0.420	-.0082353	.0197324
c_misAB	-.0016101	.0067642	-0.24	0.812	-.0148678	.0116475
c_had_tc	-.0023615	.0059267	-0.40	0.690	-.0139775	.0092546
c_cust_gt3	.0081339	.0067695	1.20	0.230	-.0051341	.0214019
c_age	-.0004214	.0001983	-2.13	0.034	-.0008101	-.0000328
c_npriarr	.0003338	.0009869	0.34	0.735	-.0016006	.0022681
c_maxsent	-.0000171	.0000135	-1.27	0.204	-.0000435	9.28e-06
cp_pri_h32	.0160407	.0115558	1.39	0.165	-.0066083	.0386896
cp_hasPriorI	.0001314	.0109404	0.01	0.990	-.0213115	.0215742
cp_lifer	-.1107783	.0679562	-1.63	0.103	-.2439701	.0224134
cp_single	-.0145285	.0092879	-1.56	0.118	-.0327324	.0036754
cp_black	-.0097422	.0122128	-0.80	0.425	-.0336789	.0141944
cp_latino	-.0151873	.0168465	-0.90	0.367	-.0482058	.0178311
cp_urban	.0045725	.0092963	0.49	0.623	-.0136479	.0227929
cp_18under~r	-.0095927	.0094668	-1.01	0.311	-.0281472	.0089618
cp_p_iq	-.0003435	.0003167	-1.08	0.278	-.0009642	.0002773
cp_p_hsgrad	.0052692	.0090456	0.58	0.560	-.0124598	.0229982
cp_p_had_job	-.0019678	.0116945	-0.17	0.866	-.0248886	.0209529
cp_p_usvet	.0048106	.0151751	0.32	0.751	-.024932	.0345532
cp_p_medlim	-.0116265	.010352	-1.12	0.261	-.031916	.0086629
cp_p_prob~al	-.0181425	.012398	-1.46	0.143	-.042442	.0061571
cp_p_prob~pe	-.004639	.0089707	-0.52	0.605	-.0222213	.0129433
cp_p_prob_mh	.0037689	.0101226	0.37	0.710	-.0160709	.0236088
cp_p_prob_~c	-.0188715	.0193018	-0.98	0.328	-.0567024	.0189594
cp_misAB	-.0045418	.0101794	-0.45	0.655	-.024493	.0154094
cp_had_tc	.0141227	.0117525	1.20	0.229	-.0089118	.0371572
cp_cust_gt3	-.0037498	.0112276	-0.33	0.738	-.0257555	.0182559
cp_age	-.0007775	.0005271	-1.48	0.140	-.0018106	.0002556
cp_npriarr	-.0005244	.0007745	-0.68	0.498	-.0020424	.0009935
cp_maxsent	.0000464	.0000357	1.30	0.193	-.0000235	.0001163
r_rel_q2	.0203134	.0097966	2.07	0.038	.0011124	.0395144
r_rel_q3	.0268805	.0110089	2.44	0.015	.0053035	.0484575
r_rel_q4	.0362499	.0111563	3.25	0.001	.014384	.0581159
r_rel_q5	.0276901	.0095472	2.90	0.004	.0089778	.0464023
r_rel_q6	.0223663	.0093679	2.39	0.017	.0040055	.0407271
r_rel_q7	.0264087	.0104835	2.52	0.012	.0058613	.046956
r_rel_q8	.0213634	.0104484	2.04	0.041	.0008849	.0418419
tier_tt	-.0019991	.0046446	-0.43	0.667	-.0111024	.0071041
r_cell	.0022534	.0067312	0.33	0.738	-.0109396	.0154464
c_cell	-.0051584	.0053643	-0.96	0.336	-.0156722	.0053554
stretches	.0018764	.0027078	0.69	0.488	-.0034309	.0071836
r_time2rel	-5.02e-06	.0000103	-0.49	0.625	-.0000251	.0000151
pct_total_tt	-.000061	.0001756	-0.35	0.728	-.0004053	.0002832
numCellies	.0008705	.0004576	1.90	0.057	-.0000264	.0017673
cellsqft_tt	.0004225	.0002189	1.93	0.054	-6.51e-06	.0008515
_Ifac_tt_52	-.0259377	.0177577	-1.46	0.144	-.0607422	.0088668
_Ifac_tt_54	-.0183422	.0194965	-0.94	0.347	-.0565546	.0198703
_Ifac_tt_55	-.0073527	.019231	-0.38	0.702	-.0450447	.0303393
_Ifac_tt_56	-.0432176	.0182082	-2.37	0.018	-.0789051	-.0075301
_Ifac_tt_57	-.0140988	.0197469	-0.71	0.475	-.0528019	.0246043
_Ifac_tt_58	-.0379588	.0217739	-1.74	0.081	-.0806349	.0047172
_Ifac_tt_59	-.0306367	.018957	-1.62	0.106	-.0677917	.0065183

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 _Ifac_tt_60 |  -.0236037   .0177449    -1.33   0.183     -.058383    .0111756
 _Ifac_tt_61 |  -.0337944   .0234061    -1.44   0.149    -.0796696    .0120807
 _Ifac_tt_62 |   .0033749   .0220418     0.15   0.878    -.0398262    .0465761
 _Ifac_tt_63 |    .015571   .0285452     0.55   0.585    -.0403765    .0715185
 _Ifac_tt_64 |  -.0400876   .0185726    -2.16   0.031    -.0764893   -.0036859
 _Ifac_tt_65 |  -.0249669   .0243533    -1.03   0.305    -.0726986    .0227648
 _Ifac_tt_66 |  -.0139675   .0201529    -0.69   0.488    -.0534664    .0255314
 _Ifac_tt_68 |   -.012711   .0183486    -0.69   0.488    -.0486737    .0232516
 _Ifac_tt_69 |  -.0139769   .0167452    -0.83   0.404    -.0467969    .0188431
 _Ifac_tt_73 |  -.0288721   .0242519    -1.19   0.234     -.076405    .0186607
 _Ifac_tt_75 |  -.0274509   .0199803    -1.37   0.169    -.0666115    .0117098
 _Ifac_tt_76 |  -.0210211    .020262    -1.04   0.300     -.060734    .0186917
 _Ifac_tt_77 |  -.0021329   .0234609    -0.09   0.928    -.0481155    .0438496
 _Ifac_tt_78 |  -.0241084   .0166709    -1.45   0.148    -.0567828    .0085659
 _Ifac_tt_81 |   .0247211    .031817     0.78   0.437     -.037639    .0870812
           k |   .0083777   .0321839     0.26   0.795    -.0547017     .071457
       _cons |   .0901178   .0699228     1.29   0.197    -.0469283    .2271639
-------------+----------------------------------------------------------------
Mills        |
   rho1-rho0 |   -.167398   .0607323    -2.76   0.006    -.2864311   -.0483649
-------------+----------------------------------------------------------------
ATE          |
  E(Y1-Y0)@X |  -.1658606    .068105    -2.44   0.015     -.299344   -.0323772
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Reinforcing: Car Theft

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Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                      Number of obs      =     10116
Treatment Model: Probit                          Replications       =        50
------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
  r_post_h24 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Treated      |
  r_staytime |  -.0000215   .0000127    -1.70   0.090    -.0000463    3.32e-06
    r_single |  -.0087186   .0112947    -0.77   0.440    -.0308557    .0134185
     r_black |   .0107369   .0136773     0.79   0.432    -.0160702    .0375439
    r_latino |    .001372   .0161071     0.09   0.932    -.0301974    .0329413
     r_urban |  -.0193793   .0118209    -1.64   0.101    -.0425479    .0037893
r_18under_~r |   .0249514   .0089061     2.80   0.005     .0074958    .0424069
      r_p_iq |   .0002313    .000316     0.73   0.464     -.000388    .0008506
  r_p_hsgrad |  -.0104771   .0079223    -1.32   0.186    -.0260045    .0050504
 r_p_had_job |   .0060982   .0109403     0.56   0.577    -.0153443    .0275408
   r_p_usvet |  -.0133421   .0101164    -1.32   0.187    -.0331698    .0064856
  r_p_medlim |   .0070034    .011272     0.62   0.534    -.0150893     .029096
r_p_prob_s~l |   .0010341    .012258     0.08   0.933    -.0229911    .0250593
r_p_prob_e~e |   .0099364   .0095654     1.04   0.299    -.0088114    .0286841
 r_p_prob_mh |   .0249796   .0095597     2.61   0.009      .006243    .0437162
r_p_prob_d~c |  -.0095521   .0177909    -0.54   0.591    -.0444217    .0253175
     r_misAB |   .0256813   .0123839     2.07   0.038     .0014093    .0499534
    r_had_tc |  -.0117875   .0091778    -1.28   0.199    -.0297757    .0062007
  r_cust_gt3 |   .0146302   .0105906     1.38   0.167     -.006127    .0353873
       r_age |  -.0002487   .0006837    -0.36   0.716    -.0015888    .0010914
   r_npriarr |   .0027899   .0014622     1.91   0.056    -.0000759    .0056557
   r_maxsent |  -.0003643   .0001369    -2.66   0.008    -.0006326    -.000096
     c_lifer |  -.0305762   .0346728    -0.88   0.378    -.0985337    .0373812
    c_single |   .0074077   .0095942     0.77   0.440    -.0113965    .0262119
     c_black |  -.0074912   .0126535    -0.59   0.554    -.0322916    .0173093
    c_latino |  -.0151234   .0175846    -0.86   0.390    -.0495885    .0193417
     c_urban |   .0078755   .0115766     0.68   0.496    -.0148143    .0305653
c_18under_~r |   .0045431   .0111827     0.41   0.685    -.0173746    .0264608
      c_p_iq |   -.000099   .0003104    -0.32   0.750    -.0007074    .0005094
  c_p_hsgrad |   .0073721    .009034     0.82   0.414    -.0103342    .0250785
 c_p_had_job |    .004531   .0059125     0.77   0.443    -.0070573    .0161194
   c_p_usvet |   .0141694   .0153276     0.92   0.355    -.0158722     .044211
```

c_p_medlim	-.0056822	.0094573	-0.60	0.548	-.0242182	.0128539
c_p_prob_s~l	.0078984	.0130417	0.61	0.545	-.0176629	.0334597
c_p_prob_e~e	-.0190951	.0099089	-1.93	0.054	-.0385162	.0003261
c_p_prob_mh	.0099565	.0094997	1.05	0.295	-.0086626	.0285757
c_p_prob_d~c	.0149743	.0180777	0.83	0.407	-.0204574	.050406
c_misAB	-.0082937	.0094467	-0.88	0.380	-.026809	.0102215
c_had_tc	-.0108952	.0080683	-1.35	0.177	-.0267089	.0049184
c_cust_gt3	-.0064726	.0092907	-0.70	0.486	-.0246821	.0117368
c_age	.001017	.0007141	1.42	0.154	-.0003827	.0024167
c_npriarr	-.0035056	.0015137	-2.32	0.021	-.0064724	-.0005388
c_maxsent	-5.11e-06	.0000176	-0.29	0.771	-.0000395	.0000293
cp_pri_h40	.0084933	.0113796	0.75	0.455	-.0138104	.030797
cp_hasPriorI	-.0023676	.0182547	-0.13	0.897	-.0381462	.0334109
cp_lifer	-.0919995	.0934085	-0.98	0.325	-.2750768	.0910777
cp_single	-.0159058	.0177634	-0.90	0.371	-.0507213	.0189098
cp_black	.000952	.0209031	0.05	0.964	-.0400173	.0419213
cp_latino	.0031673	.021588	0.15	0.883	-.0391444	.0454789
cp_urban	.0201864	.0239764	0.84	0.400	-.0268064	.0671792
cp_18under~r	-.0124298	.0196067	-0.63	0.526	-.0508582	.0259986
cp_p_iq	.0009513	.000611	1.56	0.119	-.0002461	.0021488
cp_p_hsgrad	-.0115336	.0168971	-0.68	0.495	-.0446512	.021584
cp_p_had_job	.0009288	.0166851	0.06	0.956	-.0317735	.033631
cp_p_usvet	.0217007	.0376703	0.58	0.565	-.0521318	.0955331
cp_p_medlim	.0197711	.018964	1.04	0.297	-.0173976	.0569399
cp_p_prob~al	-.0452899	.0151618	-2.99	0.003	-.0750064	-.0155733
cp_p_prob~pe	-.0150687	.0153543	-0.98	0.326	-.0451625	.0150251
cp_p_prob_mh	-.0190672	.0180227	-1.06	0.290	-.054391	.0162566
cp_p_prob_~c	.0087629	.0273666	0.32	0.749	-.0448745	.0624004
cp_misAB	.0008948	.019902	0.04	0.964	-.0381125	.039902
cp_had_tc	-.000156	.0174837	-0.01	0.993	-.0344235	.0341115
cp_cust_gt3	.0317654	.0217631	1.46	0.144	-.0108896	.0744204
cp_age	-.0005117	.0010394	-0.49	0.623	-.0025489	.0015256
cp_npriarr	.0004848	.0012678	0.38	0.702	-.0020001	.0029697
cp_maxsent	.0000393	.0000429	0.92	0.360	-.0000448	.0001235
r_rel_q2	-.0017901	.0133708	-0.13	0.893	-.0279965	.0244162
r_rel_q3	.0090431	.014859	0.61	0.543	-.0200799	.0381662
r_rel_q4	.0079685	.0160961	0.50	0.621	-.0235794	.0395163
r_rel_q5	.0054252	.0144815	0.37	0.708	-.0229581	.0338085
r_rel_q6	.0190015	.014539	1.31	0.191	-.0094945	.0474975
r_rel_q7	.026138	.0174327	1.50	0.134	-.0080295	.0603055
r_rel_q8	.0244023	.0171565	1.42	0.155	-.0092237	.0580283
tier_tt	.0075595	.0080847	0.94	0.350	-.0082862	.0234053
r_cell	.0033023	.0098798	0.33	0.738	-.0160617	.0226663
c_cell	.0002882	.0088556	0.03	0.974	-.0170686	.0176449
stretches	.0013015	.0054505	0.24	0.811	-.0093813	.0119843
r_time2rel	.000018	.0000109	1.66	0.097	-3.27e-06	.0000394
pct_total_tt	-.0001855	.0003746	-0.50	0.620	-.0009198	.0005487
numCellies	.0005376	.0004649	1.16	0.248	-.0003737	.0014488
cellsqft_tt	.0012323	.0005815	2.12	0.034	.0000927	.002372
_Ifac_tt_52	-.0037942	.0196831	-0.19	0.847	-.0423724	.034784
_Ifac_tt_54	.0184153	.017866	1.03	0.303	-.0166015	.053432
_Ifac_tt_55	-.0119791	.0264808	-0.45	0.651	-.0638806	.0399224
_Ifac_tt_56	.045064	.0433829	1.04	0.299	-.039965	.1300929
_Ifac_tt_57	.0202827	.0231086	0.88	0.380	-.0250092	.0655747
_Ifac_tt_58	.0608342	.048822	1.25	0.213	-.0348552	.1565236
_Ifac_tt_59	.0129405	.0261456	0.49	0.621	-.038304	.0641849
_Ifac_tt_60	-.0001157	.0261577	-0.00	0.996	-.0513838	.0511525
_Ifac_tt_61	-.009854	.0195568	-0.50	0.614	-.0481845	.0284765
_Ifac_tt_62	.008789	.0244065	0.36	0.719	-.039047	.0566249
_Ifac_tt_63	.0055636	.0304294	0.18	0.855	-.054077	.0652042
_Ifac_tt_64	.014335	.0278641	0.51	0.607	-.0402776	.0689476
_Ifac_tt_65	.0089456	.0313046	0.29	0.775	-.0524102	.0703015
_Ifac_tt_66	-.0071485	.0254785	-0.28	0.779	-.0570854	.0427883
_Ifac_tt_68	.0258836	.022451	1.15	0.249	-.0181194	.0698867
_Ifac_tt_69	.0436771	.0327073	1.34	0.182	-.0204281	.1077823
_Ifac_tt_73	.0723165	.0403165	1.79	0.073	-.0067024	.1513353
_Ifac_tt_75	.0820803	.0487007	1.69	0.092	-.0133712	.1775318
_Ifac_tt_76	.0509806	.032464	1.57	0.116	-.0126477	.1146089
_Ifac_tt_77	.0372359	.0378265	0.98	0.325	-.0369028	.1113746
_Ifac_tt_78	-.0083593	.0247959	-0.34	0.736	-.0569583	.0402398

_Ifac_tt_81	.2806635	.3208375	0.87	0.382	-.3481664	.9094935
k	.0414142	.0323414	1.28	0.200	-.0219739	.1048022
_cons	-.1318847	.1296724	-1.02	0.309	-.386038	.1222685
Untreated						
r_staytime	-4.93e-06	7.12e-06	-0.69	0.489	-.0000189	9.03e-06
r_single	-.0013573	.0034053	-0.40	0.690	-.0080315	.0053169
r_black	.0030788	.0060588	0.51	0.611	-.0087963	.0149539
r_latino	.0123972	.0074184	1.67	0.095	-.0021426	.026937
r_urban	.0053085	.0033095	1.60	0.109	-.0011779	.0117949
r_18under_~r	.0006629	.0037155	0.18	0.858	-.0066194	.0079452
r_p_iq	.0001127	.0001501	0.75	0.453	-.0001814	.0004068
r_p_hsgrad	-.0018367	.0036332	-0.51	0.613	-.0089577	.0052844
r_p_had_job	.0089779	.0053436	1.68	0.093	-.0014954	.0194511
r_p_usvet	-.0006925	.003899	-0.18	0.859	-.0083343	.0069494
r_p_medlim	.0018688	.0044046	0.42	0.671	-.0067641	.0105017
r_p_prob_s~l	.0038538	.0061481	0.63	0.531	-.0081963	.0159039
r_p_prob_e~e	.0003646	.0029556	0.12	0.902	-.0054284	.0061575
r_p_prob_mh	.0036924	.003422	1.08	0.281	-.0030146	.0103995
r_p_prob_d~c	-.0005162	.0054594	-0.09	0.925	-.0112164	.0101839
r_misAB	.0052508	.0047819	1.10	0.272	-.0041214	.0146231
r_had_tc	-.0001346	.0046513	-0.03	0.977	-.0092509	.0089817
r_cust_gt3	.0060398	.004527	1.33	0.182	-.0028329	.0149125
r_age	-.0008243	.0001598	-5.16	0.000	-.0011375	-.0005111
r_npriarr	.0023276	.0004026	5.78	0.000	.0015385	.0031166
r_maxsent	-.0001453	.0000566	-2.57	0.010	-.0002561	-.0000344
c_lifer	.014357	.0140686	1.02	0.307	-.013217	.041931
c_single	.0019741	.0031444	0.63	0.530	-.0041888	.008137
c_black	-.0014218	.0045735	-0.31	0.756	-.0103857	.0075421
c_latino	-.0059627	.0050472	-1.18	0.237	-.015855	.0039297
c_urban	-.000606	.0039636	-0.15	0.878	-.0083745	.0071625
c_18under_~r	-.0009901	.0046516	-0.21	0.831	-.0101071	.0081269
c_p_iq	-.0000204	.00012	-0.17	0.865	-.0002557	.0002148
c_p_hsgrad	-.0019424	.0029464	-0.66	0.510	-.0077171	.0038324
c_p_had_job	.0011038	.0035475	0.31	0.756	-.0058492	.0080568
c_p_usvet	.0059227	.0056516	1.05	0.295	-.0051542	.0169996
c_p_medlim	-.0035425	.0039489	-0.90	0.370	-.0112823	.0041972
c_p_prob_s~l	.0010127	.0043767	0.23	0.817	-.0075655	.0095909
c_p_prob_e~e	-.0085164	.0029207	-2.92	0.004	-.014241	-.0027919
c_p_prob_mh	.0033474	.0035874	0.93	0.351	-.0036838	.0103785
c_p_prob_d~c	.007013	.0041895	1.67	0.094	-.0011982	.0152242
c_misAB	-.0016567	.0039401	-0.42	0.674	-.0093792	.0060658
c_had_tc	.0020961	.0039689	0.53	0.597	-.0056827	.009875
c_cust_gt3	.0010955	.0045876	0.24	0.811	-.0078959	.010087
c_age	.0002242	.0002912	0.77	0.441	-.0003465	.0007949
c_npriarr	-.0012585	.0009358	-1.34	0.179	-.0030925	.0005756
c_maxsent	-5.97e-06	7.90e-06	-0.76	0.450	-.0000214	9.51e-06
cp_pri_h40	.0024655	.0064802	0.38	0.704	-.0102353	.0151664
cp_hasPriorI	-.008861	.0064628	-1.37	0.170	-.0215279	.0038059
cp_lifer	-.0362268	.0284473	-1.27	0.203	-.0919825	.0195288
cp_single	-.0045873	.0063352	-0.72	0.469	-.0170039	.0078294
cp_black	.0013194	.0076015	0.17	0.862	-.0135792	.016218
cp_latino	-.0003858	.011483	-0.03	0.973	-.022892	.0221204
cp_urban	-.005621	.0074782	-0.75	0.452	-.020278	.009036
cp_18under~r	.0105929	.0073165	1.45	0.148	-.0037471	.0249329
cp_p_iq	-.0001531	.0002276	-0.67	0.501	-.0005992	.000293
cp_p_hsgrad	.0064828	.0065469	0.99	0.322	-.0063489	.0193144
cp_p_had_job	-.0013412	.0059806	-0.22	0.823	-.013063	.0103806
cp_p_usvet	-.0026564	.0100756	-0.26	0.792	-.0224042	.0170914
cp_p_medlim	-.0022578	.0064903	-0.35	0.728	-.0149786	.0104629
cp_p_prob~al	-.0080741	.0069487	-1.16	0.245	-.0216933	.0055452
cp_p_prob~pe	.0078298	.0058928	1.33	0.184	-.0037198	.0193795
cp_p_prob_mh	-.00162	.0069299	-0.23	0.815	-.0152024	.0119624
cp_p_prob_~c	.013154	.0075925	1.73	0.083	-.001727	.028035
cp_misAB	-.0001188	.0074153	-0.02	0.987	-.0146525	.0144148
cp_had_tc	.0108944	.0071147	1.53	0.126	-.0030501	.0248389
cp_cust_gt3	.00709	.0084832	0.84	0.403	-.0095367	.0237167
cp_age	.0002891	.0002796	1.03	0.301	-.000259	.0008371
cp_npriarr	-.0007024	.0004813	-1.46	0.144	-.0016458	.0002409
cp_maxsent	.0000109	.0000159	0.69	0.493	-.0000203	.0000421

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     r_rel_q2 |   .0001025   .0071034     0.01   0.988    -.0138198    .0140248
     r_rel_q3 |  -.0000331   .0053615    -0.01   0.995    -.0105415    .0104752
     r_rel_q4 |   .0024455   .0062685     0.39   0.696    -.0098405    .0147314
     r_rel_q5 |   -.001354   .0062802    -0.22   0.829     -.013663    .0109551
     r_rel_q6 |  -.0088966   .0055441    -1.60   0.109    -.0197628    .0019695
     r_rel_q7 |   .0006681   .0063227     0.11   0.916    -.0117241    .0130603
     r_rel_q8 |   .0032794   .0065247     0.50   0.615    -.0095088    .0160675
      tier_tt |  -.0069381   .0029919    -2.32   0.020    -.0128021   -.0010741
       r_cell |   .0023252   .0046131     0.50   0.614    -.0067163    .0113666
       c_cell |  -.0000382    .004705    -0.01   0.994    -.0092597    .0091834
    stretches |   .0023995    .001491     1.61   0.108    -.0005228    .0053219
   r_time2rel |   2.51e-06   7.59e-06     0.33   0.741    -.0000124    .0000174
 pct_total_tt |   -.000083   .0001191    -0.70   0.486    -.0003164    .0001503
   numCellies |   .0001483   .0002627     0.56   0.572    -.0003666    .0006632
  cellsqft_tt |   .0001708   .0001318     1.30   0.195    -.0000875    .0004291
  _Ifac_tt_52 |  -.0039407   .0075912    -0.52   0.604    -.0188192    .0109377
  _Ifac_tt_54 |  -.0128195   .0093185    -1.38   0.169    -.0310835    .0054444
  _Ifac_tt_55 |   .0035157   .0097861     0.36   0.719    -.0156647    .0226961
  _Ifac_tt_56 |   .0043863   .0130322     0.34   0.736    -.0211563    .0299288
  _Ifac_tt_57 |   .0085398   .0114406     0.75   0.455    -.0138834    .0309631
  _Ifac_tt_58 |   .0221487   .0195932     1.13   0.258    -.0162532    .0605506
  _Ifac_tt_59 |   .0138154   .0093256     1.48   0.138    -.0044626    .0320933
  _Ifac_tt_60 |  -.0038329   .0111943    -0.34   0.732    -.0257733    .0181074
  _Ifac_tt_61 |  -.0050401   .0125712    -0.40   0.688    -.0296792    .0195989
  _Ifac_tt_62 |  -.0081502   .0079337    -1.03   0.304       -.0237    .0073997
  _Ifac_tt_63 |   .0253337   .0193858     1.31   0.191    -.0126618    .0633291
  _Ifac_tt_64 |  -.0115579   .0076885    -1.50   0.133    -.0266271    .0035113
  _Ifac_tt_65 |  -.0085884   .0120335    -0.71   0.475    -.0321737    .0149968
  _Ifac_tt_66 |   -.003026   .0086203    -0.35   0.726    -.0199214    .0138695
  _Ifac_tt_68 |  -.0083405   .0084015    -0.99   0.321    -.0248072    .0081262
  _Ifac_tt_69 |   .0011018   .0076472     0.14   0.885    -.0138864    .0160901
  _Ifac_tt_73 |   .0097133   .0132928     0.73   0.465    -.0163401    .0357666
  _Ifac_tt_75 |   .0064136   .0129677     0.49   0.621    -.0190026    .0318298
  _Ifac_tt_76 |   .0006447   .0117917     0.05   0.956    -.0224666    .0237561
  _Ifac_tt_77 |  -.0041521   .0127845    -0.32   0.745    -.0292093    .0209051
  _Ifac_tt_78 |   .0052531   .0088726     0.59   0.554    -.0121369    .0226431
  _Ifac_tt_81 |   .0186091   .0173388     1.07   0.283    -.0153743    .0525925
            k |   .0408354   .0284301     1.44   0.151    -.0148866    .0965573
        _cons |  -.0117128   .0385915    -0.30   0.762    -.0873508    .0639253
-------------+----------------------------------------------------------------
Mills        |
   rho1-rho0 |   .0005788   .0423763     0.01   0.989    -.0824772    .0836348
-------------+----------------------------------------------------------------
ATE          |
  E(Y1-Y0)@X |   .0869135   .0491211     1.77   0.077    -.0093622    .1831892
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Reinforcing: Weapons

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Bootstrap replications (50)
----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5
..................................................    50

Parametric Normal MTE Model                     Number of obs      =     10116
Treatment Model: Probit                         Replications       =        50
------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
  r_post_h40 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Treated      |
  r_staytime |  -.0000113   .0000212    -0.53   0.595    -.0000528    .0000303
    r_single |  -.0089462   .0116933    -0.77   0.444    -.0318646    .0139721
     r_black |   .0484898   .0183628     2.64   0.008     .0124993    .0844803
    r_latino |  -.0015336   .0193184    -0.08   0.937     -.039397    .0363298
     r_urban |   .0536455    .009083     5.91   0.000     .0358431     .071448
r_18under_~r |   .0503704   .0129779     3.88   0.000     .0249342    .0758065
      r_p_iq |    .000269    .000306     0.88   0.379    -.0003308    .0008687
  r_p_hsgrad |   -.018176   .0086147    -2.11   0.035    -.0350604   -.0012915
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r_p_had_job	.0952218	.0148334	6.42	0.000	.0661489	.1242947
r_p_usvet	-.0097611	.0146643	-0.67	0.506	-.0385026	.0189804
r_p_medlim	.0048336	.0109299	0.44	0.658	-.0165886	.0262558
r_p_prob_s~l	.0009939	.0129703	0.08	0.939	-.0244275	.0264153
r_p_prob_e~e	.0001194	.011075	0.01	0.991	-.0215871	.0218259
r_p_prob_mh	.0015542	.010168	0.15	0.879	-.0183746	.021483
r_p_prob_d~c	.0138452	.0179081	0.77	0.439	-.0212539	.0489444
r_misAB	.0051553	.0122622	0.42	0.674	-.0188783	.0291888
r_had_tc	-.0112865	.0151144	-0.75	0.455	-.0409102	.0183371
r_cust_gt3	.0369577	.0120299	3.07	0.002	.0133794	.0605359
r_age	-.0028489	.0004772	-5.97	0.000	-.0037842	-.0019137
r_npriarr	.0054205	.0013331	4.07	0.000	.0028077	.0080333
r_maxsent	-.0004546	.0001755	-2.59	0.010	-.0007986	-.0001107
c_lifer	.0803037	.0479739	1.67	0.094	-.0137235	.1743309
c_single	-.0032502	.0101437	-0.32	0.749	-.0231315	.016631
c_black	-.0276468	.023073	-1.20	0.231	-.0728691	.0175755
c_latino	-.0140046	.0175088	-0.80	0.424	-.0483212	.020312
c_urban	-.0236351	.0246807	-0.96	0.338	-.0720084	.0247381
c_18under_~r	.0108058	.0147137	0.73	0.463	-.0180326	.0396442
c_p_iq	.0003122	.0003661	0.85	0.394	-.0004053	.0010298
c_p_hsgrad	-.0083369	.0114085	-0.73	0.465	-.0306972	.0140234
c_p_had_job	.0183673	.009178	2.00	0.045	.0003787	.0363558
c_p_usvet	.0147925	.0189533	0.78	0.435	-.0223554	.0519403
c_p_medlim	-.0131029	.0110433	-1.19	0.235	-.0347474	.0085415
c_p_prob_s~l	.0213229	.0197793	1.08	0.281	-.0174438	.0600895
c_p_prob_e~e	.0055075	.0104489	0.53	0.598	-.014972	.0259871
c_p_prob_mh	-.0128558	.0113516	-1.13	0.257	-.0351045	.009393
c_p_prob_d~c	-.0114072	.0204704	-0.56	0.577	-.0515284	.0287141
c_misAB	-.0063299	.0112613	-0.56	0.574	-.0284016	.0157419
c_had_tc	-.0045444	.0134231	-0.34	0.735	-.0308532	.0217644
c_cust_gt3	-.0019206	.010386	-0.18	0.853	-.0222768	.0184356
c_age	.0005771	.0007824	0.74	0.461	-.0009563	.0021105
c_npriarr	-.0034187	.002005	-1.71	0.088	-.0073485	.0005111
c_maxsent	-.0000474	.0000263	-1.80	0.072	-.000099	4.17e-06
cp_pri_h40	-.0046468	.0233489	-0.20	0.842	-.0504099	.0411163
cp_hasPriorI	.0256931	.0225006	1.14	0.254	-.0184072	.0697934
cp_lifer	-.1343771	.0861778	-1.56	0.119	-.3032825	.0345282
cp_single	.0596733	.0220896	2.70	0.007	.0163785	.102968
cp_black	.0168883	.0237403	0.71	0.477	-.0296419	.0634186
cp_latino	-.0089862	.0290184	-0.31	0.757	-.0658612	.0478887
cp_urban	-.0233042	.027755	-0.84	0.401	-.077703	.0310945
cp_18under~r	.0319768	.0212151	1.51	0.132	-.009604	.0735577
cp_p_iq	-.0012855	.0005965	-2.16	0.031	-.0024545	-.0001164
cp_p_hsgrad	.0042244	.0233625	0.18	0.857	-.0415654	.0500141
cp_p_had_job	-.0270945	.0155226	-1.75	0.081	-.0575182	.0033292
cp_p_usvet	.0242926	.0393319	0.62	0.537	-.0527964	.1013816
cp_p_medlim	-.0167858	.0252312	-0.67	0.506	-.0662382	.0326665
cp_p_prob~al	.0049322	.0267732	0.18	0.854	-.0475424	.0574068
cp_p_prob~pe	.0318616	.0175216	1.82	0.069	-.0024802	.0662034
cp_p_prob_mh	.034254	.0209066	1.64	0.101	-.0067221	.0752301
cp_p_prob_~c	-.0369293	.0375612	-0.98	0.326	-.1105478	.0366892
cp_misAB	-.0609467	.0211026	-2.89	0.004	-.102307	-.0195864
cp_had_tc	-.0053203	.0192476	-0.28	0.782	-.0430449	.0324043
cp_cust_gt3	-.0168145	.0179533	-0.94	0.349	-.0520024	.0183733
cp_age	-.0006833	.0015764	-0.43	0.665	-.003773	.0024064
cp_npriarr	.0008182	.0017178	0.48	0.634	-.0025486	.004185
cp_maxsent	.0000922	.0000579	1.59	0.111	-.0000213	.0002056
r_rel_q2	-.0075191	.0172316	-0.44	0.663	-.0412923	.0262542
r_rel_q3	.0140072	.0185994	0.75	0.451	-.0224469	.0504613
r_rel_q4	.036615	.0225595	1.62	0.105	-.0076008	.0808308
r_rel_q5	.0154854	.0168856	0.92	0.359	-.0176097	.0485805
r_rel_q6	.0240441	.0202421	1.19	0.235	-.0156296	.0637178
r_rel_q7	.0188655	.0240821	0.78	0.433	-.0283344	.0660655
r_rel_q8	.0401562	.0171509	2.34	0.019	.006541	.0737714
tier_tt	.0057944	.0093734	0.62	0.536	-.0125771	.0241658
r_cell	-.0078367	.0151293	-0.52	0.604	-.0374897	.0218162
c_cell	-.0114357	.0143056	-0.80	0.424	-.0394742	.0166028
stretches	.0052984	.0052341	1.01	0.311	-.0049603	.0155571
r_time2rel	.0000197	.0000172	1.15	0.251	-.0000139	.0000534
pct_total_tt	.0000759	.0005158	0.15	0.883	-.0009351	.0010869

numCellies	.0017827	.0008569	2.08	0.037	.0001033	.0034622
cellsqft_tt	.0008326	.0006988	1.19	0.233	-.000537	.0022023
_Ifac_tt_52	-.0048104	.0271009	-0.18	0.859	-.0579273	.0483064
_Ifac_tt_54	-.0023536	.0363988	-0.06	0.948	-.0736939	.0689866
_Ifac_tt_55	.0116017	.0336644	0.34	0.730	-.0543794	.0775828
_Ifac_tt_56	-.0136821	.0382881	-0.36	0.721	-.0887254	.0613612
_Ifac_tt_57	.0139892	.0356005	0.39	0.694	-.0557865	.0837648
_Ifac_tt_58	.1248524	.0466122	2.68	0.007	.0334942	.2162107
_Ifac_tt_59	-.0070613	.0271697	-0.26	0.795	-.0603129	.0461903
_Ifac_tt_60	-.0142633	.0304785	-0.47	0.640	-.074	.0454734
_Ifac_tt_61	.0742172	.0357701	2.07	0.038	.004109	.1443254
_Ifac_tt_62	.0605854	.0450784	1.34	0.179	-.0277667	.1489375
_Ifac_tt_63	.087035	.0434917	2.00	0.045	.0017929	.1722772
_Ifac_tt_64	-.0484969	.03046	-1.59	0.111	-.1081975	.0112037
_Ifac_tt_65	.0638085	.0421084	1.52	0.130	-.0187224	.1463395
_Ifac_tt_66	.0108613	.0367528	0.30	0.768	-.0611729	.0828954
_Ifac_tt_68	-.0083021	.0301244	-0.28	0.783	-.0673449	.0507407
_Ifac_tt_69	.0469672	.0387194	1.21	0.225	-.0289214	.1228558
_Ifac_tt_73	.0159474	.0465271	0.34	0.732	-.0752439	.1071388
_Ifac_tt_75	-.0068087	.0364573	-0.19	0.852	-.0782637	.0646463
_Ifac_tt_76	.0266297	.0481495	0.55	0.580	-.0677415	.1210009
_Ifac_tt_77	-.0146098	.0373197	-0.39	0.695	-.087755	.0585354
_Ifac_tt_78	-.0077908	.0264539	-0.29	0.768	-.0596395	.0440579
_Ifac_tt_81	-.0137403	.0428781	-0.32	0.749	-.0977798	.0702992
k	.0934917	.0497807	1.88	0.060	-.0040767	.1910601
_cons	.1481766	.1398892	1.06	0.289	-.1260012	.4223545
Untreated						
r_staytime	.0000225	.0000129	1.74	0.081	-2.80e-06	.0000477
r_single	-.0006014	.0069378	-0.09	0.931	-.0141991	.0129964
r_black	.0632044	.0121769	5.19	0.000	.0393381	.0870706
r_latino	.016698	.0128929	1.30	0.195	-.0085717	.0419676
r_urban	.0230864	.0071045	3.25	0.001	.0091618	.037011
r_18under_~r	.0440804	.0103106	4.28	0.000	.023872	.0642889
r_p_iq	-.0003668	.0002158	-1.70	0.089	-.0007899	.0000562
r_p_hsgrad	-.0094338	.0074149	-1.27	0.203	-.0239667	.0050992
r_p_had_job	.0843586	.0129096	6.53	0.000	.0590563	.1096609
r_p_usvet	.0123714	.0091462	1.35	0.176	-.0055548	.0302976
r_p_medlim	.0049686	.0090842	0.55	0.584	-.0128361	.0227733
r_p_prob_s~l	-.036861	.0124135	-2.97	0.003	-.061191	-.0125309
r_p_prob_e~e	.0198978	.0083488	2.38	0.017	.0035344	.0362611
r_p_prob_mh	.0106214	.0069019	1.54	0.124	-.0029061	.0241489
r_p_prob_d~c	-.0275516	.0116227	-2.37	0.018	-.0503315	-.0047716
r_misAB	.0206981	.0118806	1.74	0.081	-.0025874	.0439836
r_had_tc	-.0027751	.011481	-0.24	0.809	-.0252773	.0197272
r_cust_gt3	.0282548	.0106731	2.65	0.008	.007336	.0491737
r_age	-.0024703	.0004033	-6.12	0.000	-.0032608	-.0016797
r_npriarr	.0040639	.0010385	3.91	0.000	.0020286	.0060993
r_maxsent	-.0004317	.0001196	-3.61	0.000	-.0006661	-.0001973
c_lifer	.0861762	.0531583	1.62	0.105	-.0180121	.1903646
c_single	-.0117571	.0080786	-1.46	0.146	-.0275908	.0040766
c_black	-.0160251	.0175924	-0.91	0.362	-.0505056	.0184554
c_latino	.0076361	.0121777	0.63	0.531	-.0162317	.0315038
c_urban	-.0213082	.0146927	-1.45	0.147	-.0501054	.0074891
c_18under_~r	-.0071446	.0121166	-0.59	0.555	-.0308927	.0166036
c_p_iq	.0002586	.0002836	0.91	0.362	-.0002972	.0008144
c_p_hsgrad	-.006953	.0086497	-0.80	0.421	-.0239061	.0100001
c_p_had_job	-.0111075	.0083687	-1.33	0.184	-.0275098	.0052948
c_p_usvet	-.0088691	.0110404	-0.80	0.422	-.0305078	.0127697
c_p_medlim	-.0105542	.0086868	-1.21	0.224	-.02758	.0064716
c_p_prob_s~l	.021882	.0112917	1.94	0.053	-.0002494	.0440134
c_p_prob_e~e	.0027427	.0075123	0.37	0.715	-.0119812	.0174665
c_p_prob_mh	-.0010242	.006978	-0.15	0.883	-.0147009	.0126525
c_p_prob_d~c	-.0174411	.0108976	-1.60	0.109	-.0387999	.0039177
c_misAB	.0057556	.0085967	0.67	0.503	-.0110935	.0226048
c_had_tc	.0048121	.0078294	0.61	0.539	-.0105332	.0201574
c_cust_gt3	-.0103667	.0087032	-1.19	0.234	-.0274246	.0066912
c_age	.0003636	.0004406	0.83	0.409	-.0005001	.0012272
c_npriarr	-.0029739	.0018342	-1.62	0.105	-.0065688	.000621
c_maxsent	-.0000591	.0000316	-1.87	0.061	-.000121	2.78e-06

cp_pri_h40	-.0157554	.0178592	-0.88	0.378	-.0507589	.019248
cp_hasPriorI	-.0080574	.0164479	-0.49	0.624	-.0402947	.0241799
cp_lifer	-.0433324	.1017551	-0.43	0.670	-.2427687	.1561039
cp_single	-.0110678	.0141396	-0.78	0.434	-.0387809	.0166454
cp_black	-.0022456	.0193886	-0.12	0.908	-.0402465	.0357554
cp_latino	-.0141879	.025875	-0.55	0.583	-.064902	.0365262
cp_urban	.0107096	.0163869	0.65	0.513	-.0214081	.0428272
cp_18under~r	-.0196665	.016842	-1.17	0.243	-.0526763	.0133433
cp_p_iq	-.0001285	.0005393	-0.24	0.812	-.0011855	.0009285
cp_p_hsgrad	-.0014539	.0155427	-0.09	0.925	-.0319171	.0290093
cp_p_had_job	-.0215363	.0139358	-1.55	0.122	-.04885	.0057773
cp_p_usvet	.009674	.0309975	0.31	0.755	-.0510799	.0704279
cp_p_medlim	.0079771	.0157026	0.51	0.611	-.0227995	.0387536
cp_p_prob~al	-.0185985	.0171742	-1.08	0.279	-.0522593	.0150623
cp_p_prob~pe	.0162819	.0162837	1.00	0.317	-.0156336	.0481974
cp_p_prob_mh	.0036612	.0126461	0.29	0.772	-.0211248	.0284471
cp_p_prob_~c	-.0058332	.023907	-0.24	0.807	-.0526901	.0410236
cp_misAB	-.0286223	.0154248	-1.86	0.064	-.0588544	.0016098
cp_had_tc	.0159467	.0212731	0.75	0.453	-.0257479	.0576413
cp_cust_gt3	-.0024445	.0159938	-0.15	0.879	-.0337919	.0289028
cp_age	-.001	.000808	-1.24	0.216	-.0025836	.0005836
cp_npriarr	.0006378	.0013807	0.46	0.644	-.0020684	.0033439
cp_maxsent	.0000834	.0000556	1.50	0.134	-.0000256	.0001924
r_rel_q2	.0023788	.0135708	0.18	0.861	-.0242195	.0289771
r_rel_q3	.0476471	.0172107	2.77	0.006	.0139147	.0813794
r_rel_q4	.0534188	.018134	2.95	0.003	.0178768	.0889607
r_rel_q5	.036302	.0173333	2.09	0.036	.0023293	.0702747
r_rel_q6	.0465332	.0178967	2.60	0.009	.0114563	.0816102
r_rel_q7	.0460437	.0164304	2.80	0.005	.0138408	.0782466
r_rel_q8	.0487541	.0159866	3.05	0.002	.017421	.0800872
tier_tt	.000582	.0063105	0.09	0.927	-.0117865	.0129504
r_cell	.0112871	.0073397	1.54	0.124	-.0030983	.0256726
c_cell	-.0082864	.0081363	-1.02	0.308	-.0242332	.0076605
stretches	-.0018774	.0038406	-0.49	0.625	-.0094047	.00565
r_time2rel	-4.05e-06	.0000132	-0.31	0.758	-.0000299	.0000218
pct_total_tt	-.0002241	.0002671	-0.84	0.401	-.0007475	.0002993
numCellies	.0005534	.0006717	0.82	0.410	-.0007631	.00187
cellsqft_tt	.0005199	.0003638	1.43	0.153	-.0001932	.0012329
_Ifac_tt_52	.0168317	.0160383	1.05	0.294	-.0146027	.0482661
_Ifac_tt_54	-.0137915	.0204572	-0.67	0.500	-.0538869	.026304
_Ifac_tt_55	.015867	.0247019	0.64	0.521	-.0325478	.0642818
_Ifac_tt_56	-.0293955	.026136	-1.12	0.261	-.080621	.0218301
_Ifac_tt_57	.0025122	.0212879	0.12	0.906	-.0392113	.0442356
_Ifac_tt_58	-.0170668	.0287559	-0.59	0.553	-.0734272	.0392937
_Ifac_tt_59	-.0124711	.0181265	-0.69	0.491	-.0479984	.0230563
_Ifac_tt_60	.0099937	.021047	0.47	0.635	-.0312578	.0512451
_Ifac_tt_61	.0061074	.029717	0.21	0.837	-.0521368	.0643517
_Ifac_tt_62	.0309029	.0271709	1.14	0.255	-.0223511	.0841569
_Ifac_tt_63	.0102617	.0409844	0.25	0.802	-.0700662	.0905895
_Ifac_tt_64	.0120048	.0248641	0.48	0.629	-.036728	.0607377
_Ifac_tt_65	.0252736	.0303683	0.83	0.405	-.0342472	.0847944
_Ifac_tt_66	.0106886	.0224689	0.48	0.634	-.0333496	.0547268
_Ifac_tt_68	-.0001579	.0277003	-0.01	0.995	-.0544493	.0541336
_Ifac_tt_69	.0129717	.019054	0.68	0.496	-.0243734	.0503169
_Ifac_tt_73	.0166939	.0326943	0.51	0.610	-.0473859	.0807736
_Ifac_tt_75	-.0137902	.0231394	-0.60	0.551	-.0591425	.0315621
_Ifac_tt_76	.0211715	.0221596	0.96	0.339	-.0222605	.0646035
_Ifac_tt_77	.0157612	.0305209	0.52	0.606	-.0440588	.0755811
_Ifac_tt_78	.0339575	.0214747	1.58	0.114	-.0081321	.076047
_Ifac_tt_81	.0511166	.0360771	1.42	0.157	-.0195932	.1218264
k	.0725357	.0491887	1.47	0.140	-.0238724	.1689438
_cons	.0767964	.074667	1.03	0.304	-.0695482	.2231409
Mills						
rho1-rho0	.0209561	.0708388	0.30	0.767	-.1178854	.1597975
ATE						
E(Y1-Y0)@X	.1446381	.0586013	2.47	0.014	.0297818	.2594945

Appendix E: Parametric and Semiparametric Marginal Prison Peer Effect Estimates (Tables)

Table E1

Rearrest and Reincarceration: Heterogeneity and Prison Peer Effect Estimates				
	Essential Heterogeneity and Average Prison Peer Effects			
		Coefficient	Bootstrap SE	p
Rearrested	*IV = % Open Beds, Cellie Time In, Same Race & County*			
	APPE (P)	-0.0682	0.0836	0.414
	APPE (SP)	-0.1102	0.1299	0.396
Reincarcerated	*IV = % Open Beds, Cellie Time In, Same Race & County*			
	APPE (P)	-0.0665	0.0781	0.394
	APPE (SP)	-0.0858	0.1054	0.416
Rearrested OR Reincarcerated	*IV = % Open Beds, Cellie Time In, Same Race & County*			
	APPE (P)	-0.0646	0.0935	0.489
	APPE (SP)	-0.1710	0.1363	0.210
Rearrested AND Reincarcerated	*IV = % Open Beds, Cellie Time In, Same Race & County*			
	APPE (P)	-0.0701	0.0746	0.347
	APPE (SP)	-0.0262	0.1092	0.810
	D= Cellmate Prior Incarceration			

Table E2

Switching Prison Peer Effect Estimates (Cellie Had Prior Arrest for Crime Type, Releasee Did Not)					
		Essential Heterogeneity and Average Prison Peer Effects			
			Coefficient	Bootstrap SE	p
Type P Crimes	Drug	*IV = % Open Beds, Cellie Time In, Same Race*			
	n=3,415*	APPE (P)	0.0372	0.0636	0.558
		APPE (SP)	0.0672	0.0639	0.293
		Includes cubic terms			
		APPE (P)	0.1144	0.1091	0.294
		APPE (SP)	0.0202	0.1033	0.845
Type Q Crimes	Contempt	*IV = % Open Beds, Cellie Time In*			
	n=7,310*	APPE (P)	-0.0273	0.0951	0.774
		APPE (SP)	-0.0475	0.1365	0.728
	Drugs	*IV = % Open Beds, Cellie Time In, Same Race*			
	n=3,409*	APPE (P)	0.0384	0.0561	0.494
		APPE (SP)	0.0699	0.0691	0.312
		Includes cubic terms			
		APPE (P)	0.1051	0.0892	0.239
		APPE (SP)	0.0147	0.1133	0.897
	Homicide	*IV = % Open Beds, Cellie Time In, Same Race*			
	n=9,229*	APPE (P)	-0.0589	0.0298	0.048
		APPE (SP)	-0.1692	0.0481	0.000
	Robbery	*IV = % Open Beds, Cellie Time In, Same Race*			
	n=7,551*	APPE (P)	-0.1659	0.0681	0.015
		APPE (SP)	-0.1841	0.1197	0.124

* Switching effects are possible only for releasees who do not have any prior offenses of the specified crime type

Table E3

Reinforcing Prison Peer Effect Estimates (Cellie and Releasee Had Prior Arrest for Crime Type)					
		Essential Heterogeneity and Average Prison Peer Effects			
			Coefficient	Bootstrap SE	p
Type P Crimes	Drug n=6,701*	*IV = % Open Beds, Cellie Time In, Same Race*			
		APPE (P)	0.0350	0.0546	0.522
		APPE (SP)	0.0672	0.0639	0.293
		IV = % Open Beds, Cellie Time In, Same County			
		APPE (P)	0.0512	0.0560	0.360
		APPE (SP)	0.1131	0.0705	0.108
	Inchoate n=4,799*	*IV = % Open Beds, Cellie Time In, Same Race*			
		APPE (P)	-0.0147	0.0745	0.843
		APPE (SP)	-0.0113	0.0775	0.884
		IV = % Open Beds, Cellie Time In, Same County			
		APPE (P)	0.0550	0.0640	0.391
		APPE (SP)	0.1808	0.0940	0.055
Type Q Crimes	Assault n=5,561*	*IV = % Open Beds, Cellie Time In, Same Race*			
		APPE (P)	0.0054	0.1950	0.978
		APPE (SP)	0.6087	0.3726	0.102
	Drugs n=6,707*	*IV = % Open Beds, Cellie Time In, Same Race*			
		APPE (P)	0.0357	0.0549	0.515
		APPE (SP)	0.0699	0.0751	0.353
		IV = % Open Beds, Cellie Time In, Same County			
		APPE (P)	0.0500	0.0480	0.298
		APPE (SP)	0.1124	0.0650	0.084
	Car Theft n=1,799*	*IV = % Open Beds, Cellie Time In, Same Race*			
		APPE (P)	0.0869	0.0491	0.077
		APPE (SP)	0.0478	0.0752	0.525
	Weapons n=3,593*	*IV = % Open Beds, Cellie Time In, Same Race*			
		APPE (P)	0.1446	0.0586	0.014
		APPE (SP)	0.1561	0.0706	0.027

* Reinforcing effects are possible only for releasees who have at least one prior offense of the specified crime type

Appendix F: Parametric and Semiparametric Marginal Prison Peer Effect Estimates (Select Figures)

Figure F1

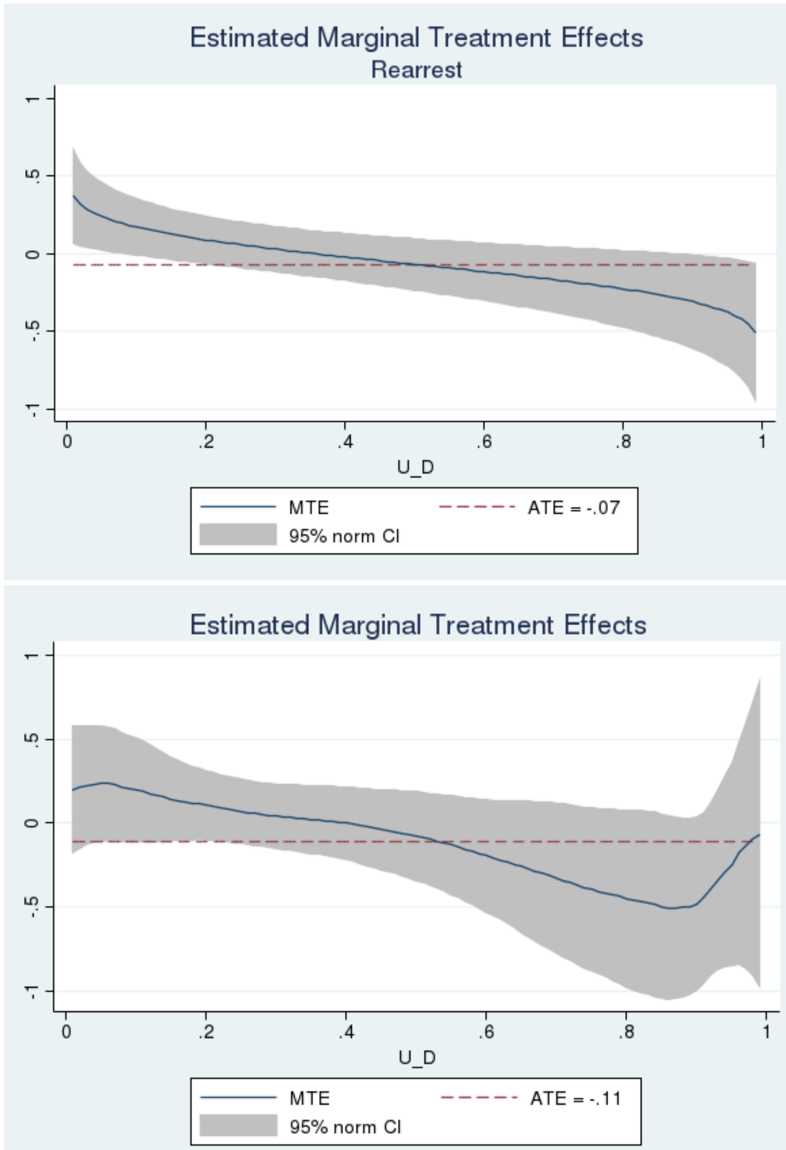
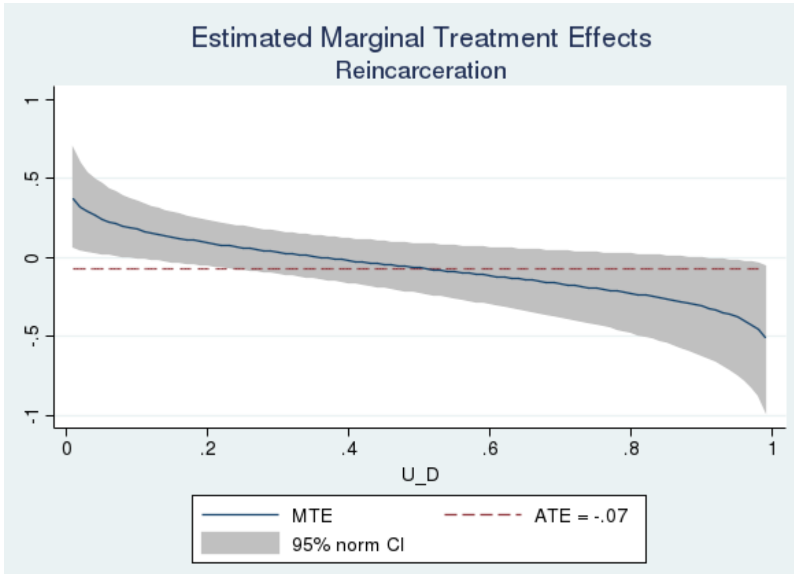
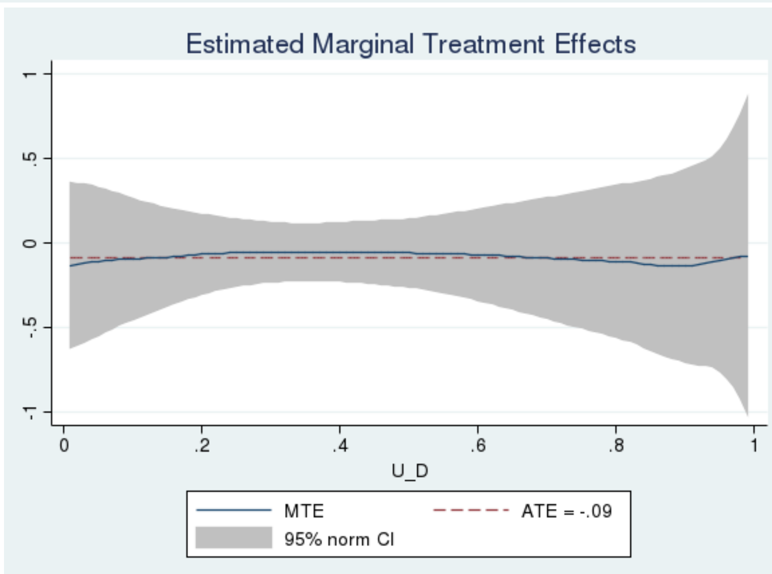


Figure F2

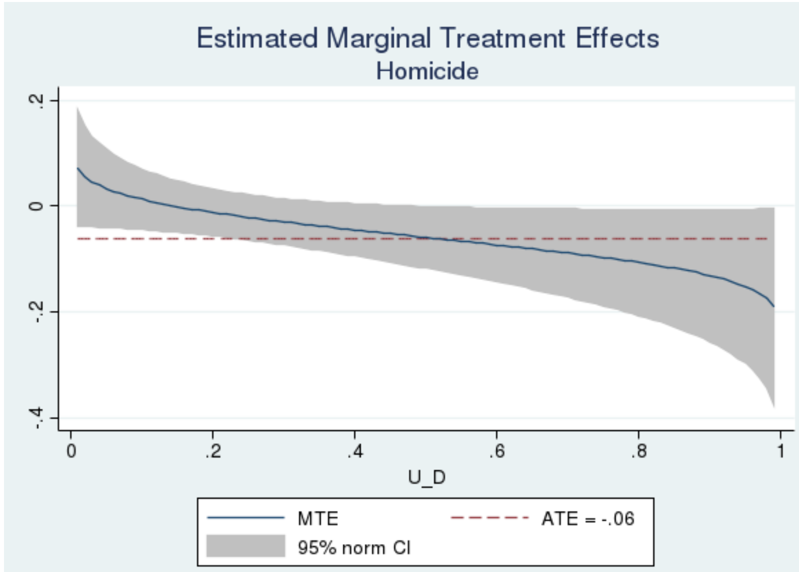


Estimated Marginal Treatment Effects
Reincarceration
1
.5
0
-.5
-1
0
.2
.4
.6
.8
1
U_D
MTE
ATE = -.07
95% norm CI



Estimated Marginal Treatment Effects
1
.5
0
-.5
-1
0
.2
.4
.6
.8
1
U_D
MTE
ATE = -.09
95% norm CI

Figure F3


Estimated Marginal Treatment Effects
Homicide
.2
0
-.2
-.4
0
.2
.4
.6
.8
1
U_D
MTE
ATE = -.06
95% norm CI

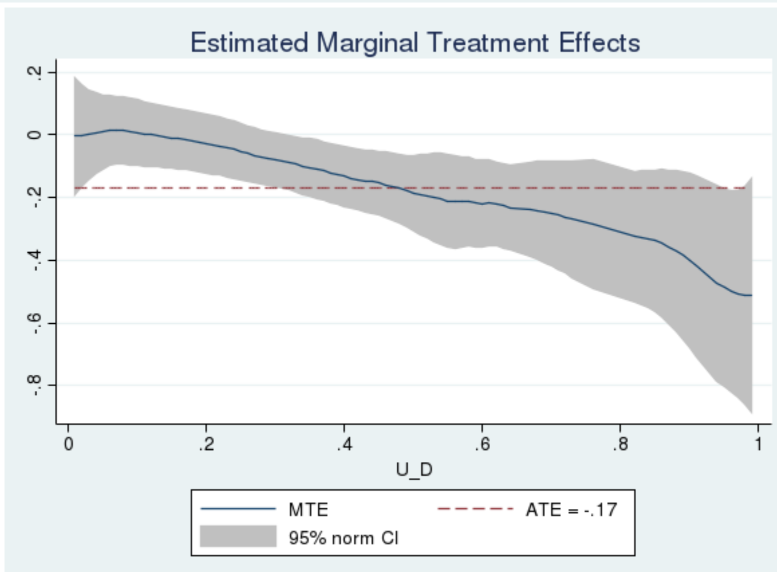
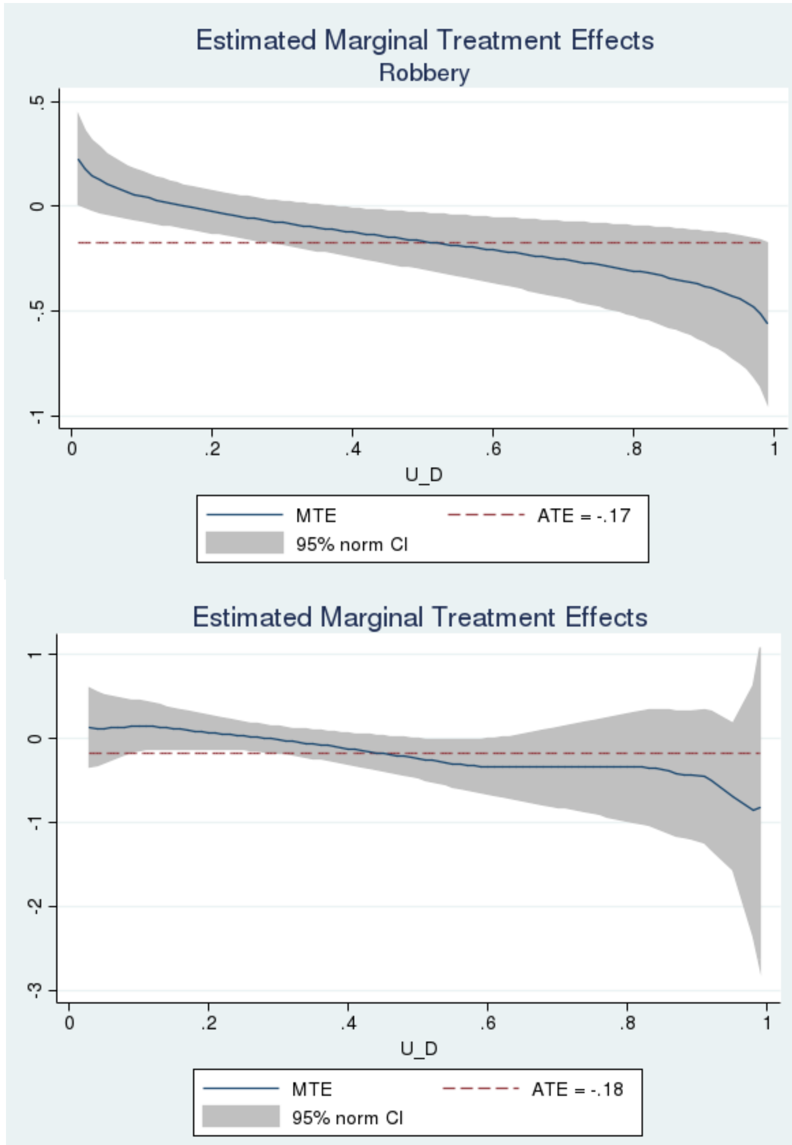
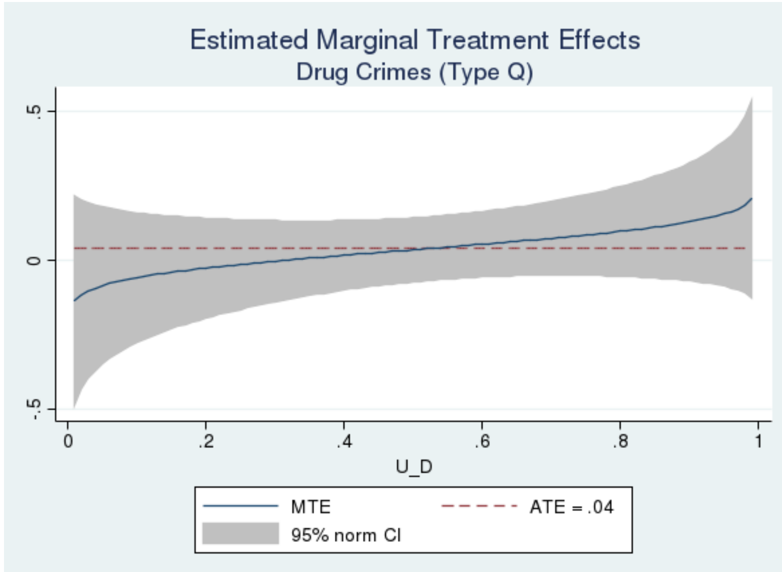

Estimated Marginal Treatment Effects
.2
0
-.2
-.4
-.6
-.8
0
.2
.4
.6
.8
1
U_D
MTE
ATE = -.17
95% norm CI

Figure F4



Estimated Marginal Treatment Effects
Robbery
.5
0
-.5
-1
0
.2
.4
.6
.8
1
U_D
MTE
ATE = -.17
95% norm CI
Estimated Marginal Treatment Effects
1
0
-1
-2
-3
0
.2
.4
.6
.8
1
U_D
MTE
ATE = -.18
95% norm CI

Figure F5


Estimated Marginal Treatment Effects
Drug Crimes (Type Q)
.5
0
-.5
0
.2
.4
.6
.8
1
U_D
MTE
ATE = .04
95% norm CI

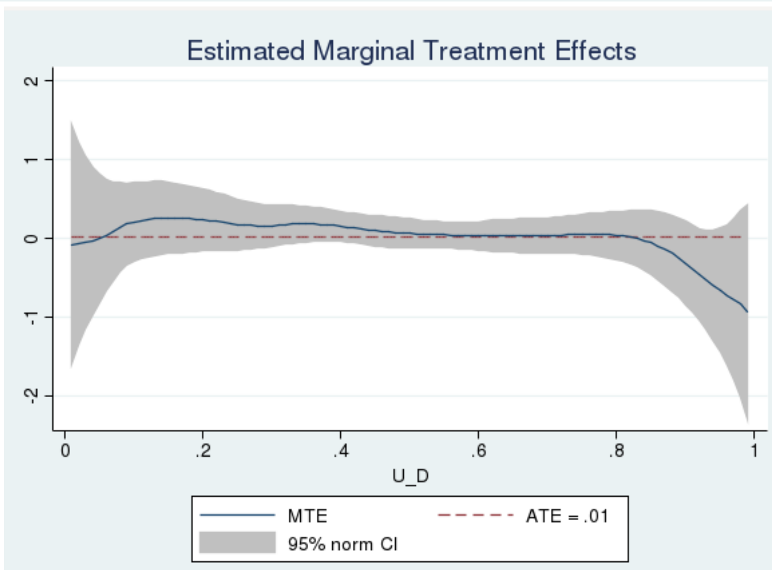
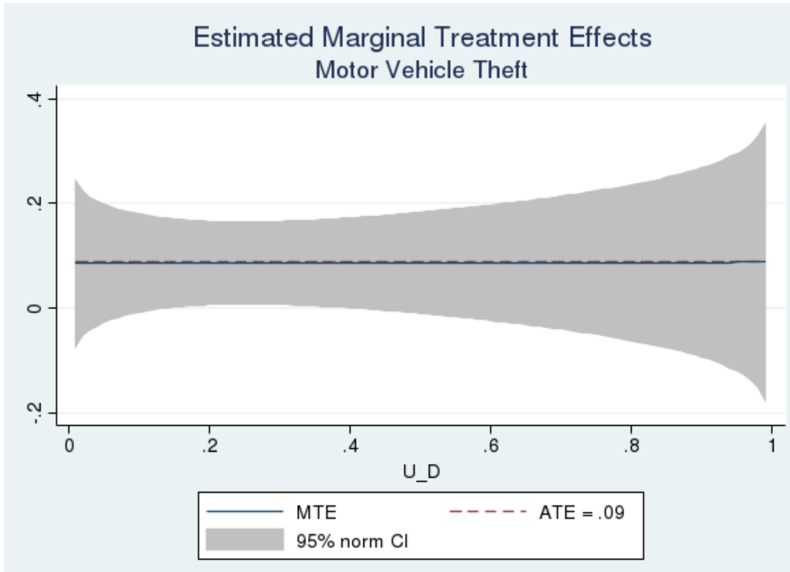

Estimated Marginal Treatment Effects
2
1
0
-1
-2
0
.2
.4
.6
.8
1
U_D
MTE
ATE = .01
95% norm CI

Figure F6


Estimated Marginal Treatment Effects
Motor Vehicle Theft
-.2
0
.2
.4
0
.2
.4
.6
.8
1
U_D
MTE
ATE = .09
95% norm CI

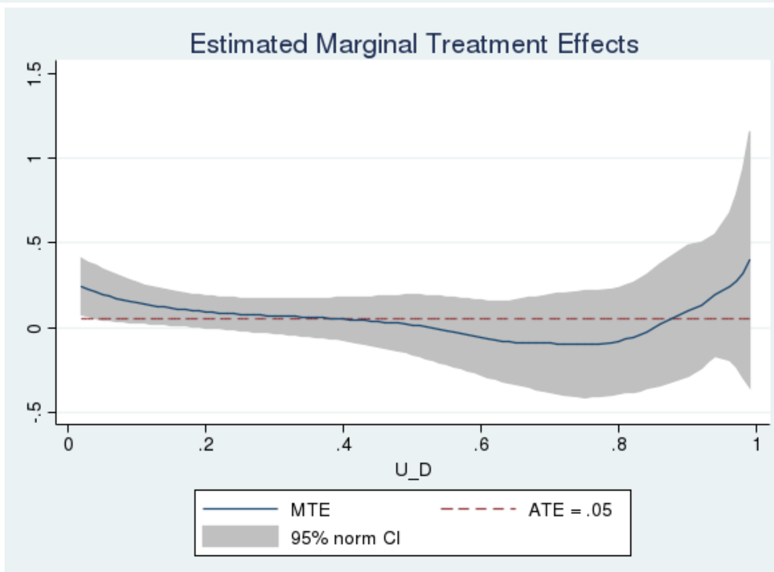
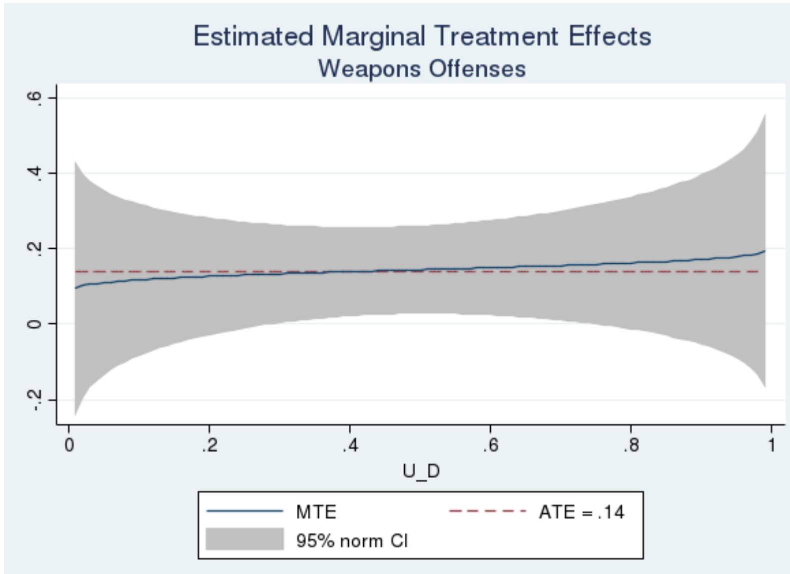
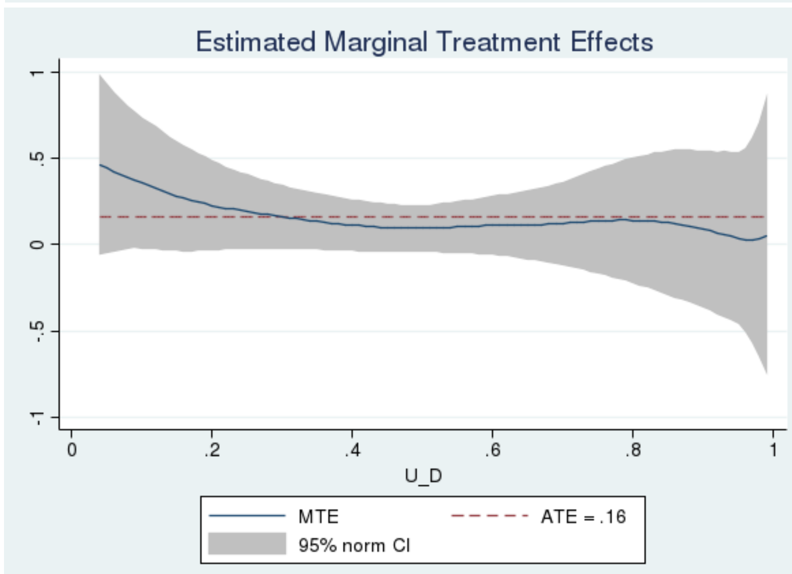

Estimated Marginal Treatment Effects
-.5
0
.5
1
1.5
0
.2
.4
.6
.8
1
U_D
MTE
ATE = .05
95% norm CI

Figure F7



Estimated Marginal Treatment Effects
Weapons Offenses
-.2
0
.2
.4
.6
0
.2
.4
.6
.8
1
U_D
MTE
ATE = .14
95% norm CI



Estimated Marginal Treatment Effects
-1
-.5
0
.5
1
0
.2
.4
.6
.8
1
U_D
MTE
ATE = .16
95% norm CI

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