Early Release from Prison and Recidivism: A Regression Discontinuity Approach*

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Abstract

The prison system in most developed countries is faced with two major problems: overcrowding and high recidivism rates after release. Early discharge of prisoners on electronic monitoring or 'tag' has become a popular policy to try and solve both these problems. It is difficult to show that is has an impact on future criminal behaviour as there are important selection issues since the best behaved inmates are usually the ones to be released early. In the paper I exploit an administrative rule which makes offenders sentenced to less than three months in prison ineligible for the Home Detention Curfew (HDC) scheme in England and Wales to try and estimate the impact of early release on recidivism. As we have extremely detailed administrative data we obtain OLS and then RD results controlling and matching on observable characteristics. All models generate estimates of a strong impact of HDC on recidivism which decreases by almost a fifth. The similarity of the results would suggest most of the selection is on observable and early release from prison on tags is a very successful policy although this must be interpreted with care due to the fuzzy nature of the discontinuity.

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1. Introduction

The issue of early release from prison remains a highly charged and contentious issue, especially with pressures on prison crowding and questions to do with re-integrating offenders back into society. The Home Detention Curfew (HDC) scheme was introduced in January 1999 to the whole of England and Wales. Prisoners sentenced for at least three month and no more than four years were made eligible to early release on an electronic monitored curfew for up to 50 percent of their sentence provided they pass a risk assessment and are able to give a suitable residential address. Although the scheme has been going on for eight years now, a recent House of Commons Committee of Public Accounts report concluded that:

> "There is insufficient evidence available to determine whether electronic monitoring helps to reduce re-offending or promote rehabilitation. The Home Office should carry out further research to establish the role that electronic monitoring could play in minimising re-offending. It should make the results of the research available to courts and prisons, which make decisions on whether to place offenders on curfews."[†]

In this paper I look at the impact of HDC participation on re-offending rates. We do so using state of the art statistical modelling methods which consider who gets selected for early release through HDC and evaluates the impact on subsequent re-offending for individuals participating in HDC schemes as compared to those who do not participate.

The structure of the report is as follows. It begins in Section 2 by first briefly discussing the HDC scheme and then focussing on issues to do with eligibility for selection and the modelling approach we adopt to take into account this selection. In Section 3 we offer a description of the data we use and present some descriptive statistics. Section 4 presents the results from the statistical modelling. Section 5 contains and a discussion of the main findings and other concluding remarks

[†] House of Commons Committee of Public Accounts (2006) "The Electronic Monitoring of Adult Offenders", Conclusion 6, p.4

2. The HDC Scheme, Issues of Selection and Modelling Approach

The Home Detention Curfew (HDC) Scheme

The Home Detention Curfew (HDC) scheme applies to prisoners who are serving sentences of between three months and under four years. It allows prisoners to live outside of prison providing they do not breach the rules of their curfew and is designed to help prisoners prepare for life after their release. Prisoners released on HDC had to sign a licence enforcing the times when they have to remain at their home address or hostel (this is normally 7pm – 7am). An electronic tag is fitted to the prisoner and monitoring equipment installed at the address by a private contractor.

Table 1 describes the salient features of the HDC scheme in terms of sentence length, custodial period and the time spent on HDC. There are clear cut-off periods for HDC eligibility and the time spent on HDC. These clear, discrete, cut-off thresholds are important for our research approach for modelling HDC, which we describe below.

Table 1: Sentence Length, Custodial Period, and Period on HDC

Length of Sentence	**Custodial Period of Sentence**	**Custodial Period to be Served if HDC Granted**	**Period on HDC**
< 3 Months	< 6 Weeks	Not eligible	-
3 Months	6 Weeks	4 Weeks	2 Weeks
6 Months	3 Months	6 Weeks	6 Weeks
12 Months	6 Months	3 Months	3 Months
18 Months	9 Months	4.5 Months	4.5 Months
2 Years	1 Year	7.5 Months	4.5 Months
< 4 Years	< 2 Years	1 Year 7.5 Months	4.5 Months
> 4 Years	> 2 Years	Not eligible	-

The majority of offenders are, at least in principle, considered for early release on HDC. However, there are a number of statutory exclusions (in addition to the sentence time limit) as: i) HDC is only available to adults[‡]; and ii) individuals who have committed sexual offences or breached temporary release or curfew orders cannot be considered for the scheme. Most other prisoners are theoretically eligible for early release on HDC, but must first be assessed according to the two following essential criteria:

a) Pass a risk assessment conducted by the prison where the detainee is held. This takes into account previous offending history and other behavioural attributes which could indicate that the prisoner may be likely to breach trust (e.g. breach of bail conditions). The prison staff also looks at the general behaviour of the offender while incarcerated and participation in offending behaviour programs. All these elements are taken into account to ascertain low risk of re-offending for eligibility for early release on HDC.

b) The need to have an appropriate address is required by the National Probation Services which provides a home circumstances report. This mainly checks that the proposed curfew address is suitable, the risk of the prisoner to the public and/or victims, and of re-offending at this address are acceptable. This is then passed on to the prison which will make a final decision on HDC eligibility.

If at any stage in this assessment it becomes apparent that the individual is not eligible for HDC, the process is stopped and the prisoner will serve the rest of his/her time in prison. In practice a total an average of 35 percent of offenders, among those not automatically excluded for consideration, were released early and spent the end of their sentence on electronic monitoring curfew between 2000 and 2006. This represents a substantial number of prisoners going through the HDC scheme but there is no, to our knowledge, evaluation of the impact it has on future criminal behaviour. This is an important question as over 50 percent of discharged prisoners re-offend within one year of release.

Issues of Selection and Modelling Approach

The main reason why the impact of HDC on recidivism has not yet been consistently estimated is mainly because there are important selection issues for participation in the scheme which are very likely to bias estimation attempts that do not consider them. The brief description on eligibility above makes it clear, for example, that

[‡] Availability was extended to under 18's in July 2003.

HDC is more likely to be granted to offenders with low risks of re-offending. From a modelling perspective, this means that the selection process for the scheme is certainly going to influence the outcome variable we are interested in, namely the probability of re-offending.

Conceptually an ideal empirical comparison would compare the probability of a prisoner of committing a crime after release of an offender who was selected for early release on HDC to one *as identical as possible* who remained in custody until the end of his/her sentence. However, in a practical sense, even with rich data that could control for a large number of observable characteristics of offenders it is very clear in the case of HDC that some of the decisions on eligibility to the scheme are discretionary (e.g. prison staff opinion of prisoner behaviour). We therefore need to incorporate this 'selection on unobservables' aspect into our empirical analysis.

Methodology

The main modelling problem we face in estimating the impact of HDC on recidivism is that (both observable and unobservable) characteristics of offenders which are used to decide eligibility are also likely to influence re-offending. This is especially true in terms of unobservable characteristics during the selection process. With this in mind we consider two methodologies, the first being Ordinary Least Squares (OLS) regression methods coupled with Propensity Score Matching (PSM) where we can consider selection on observables, the second using Regression Discontinuity Design (RDD) which potentially can also deal with the selection on unobservables issue. We consider each of these in turn:

1). OLS and OLS with PSM

For individual i a simple statistical model relating recidivism, our outcome of interest, to HDC participation can be written as:

$$REC_i = \alpha + \beta HDC_i + u_i \quad (1)$$

where *REC* measures recidivism, *HDC* is a dummy variable for program participation and u is an error term. If assignment to HDC treatment was random, then β would be an unbiased estimator of the impact of *HDC* on re-offending.

However, it is self-evident that HDC participation is non-random and so a regression estimate from equation (1) will be biased. One possible means to deal with this is to augment (1) by adding observable characteristics of prisoners to amend the equation as

$$REC_i = \alpha + \beta HDC_i + \gamma_k X_{ki} + u_i \tag{2}$$

where *k* individual characteristic are included in the vector of control variables, *X*. The Ordinary Least Squares (OLS) estimate of β is then the relationship between *REC* and *HDC* holding constant the X's. However, if selection into HDC is dependent on factors not in X, problems remain.

One popular method to attempt to solve this problem in program evaluation has been to resort to Propensity Score Matching (PSM). This can allow for selection on observables in X to occur in a more flexible manner than in (2). It is important to stress, however, that it cannot deal with selection on unobservables.

The PSM method gives a score of the probability of participation into the program based on a set of observable characteristics to each of the individuals. This is estimated using the following probit equation:

$$\Pr[HDC = 1]_i = \Phi(\alpha + \delta X_{ki}) \tag{3}$$

where $\Phi(.)$ is the standard normal cumulative distribution function.

Equation (3) is a probit estimation of HDC participation on the characteristics in *X*. From (3) one generates propensity scores for each individual. These scores can be used to match prisoners which have not been released on HDC to others who were selected for the scheme with a similar score or the 'nearest neighbour' score (i.e. who are similar in terms of the *X*'s). Once this is done we can again run a version of equation (2) to obtain an estimate of β but this time re-weighting each non-treated individual depending on how similar they are to their treated match. While again this should generate estimates of β more precise than the two first models, it is still likely to suffer from bias.

The reason is that even after matching on, and controlling for, observable individual characteristics, there remains the problem of program selection on unobservable characteristics. Formally, we may still have that $E[u|HDC] \neq 0$ or that the unobserved part that remains in the error term *u* is still correlated with the participation decision *HDC*. A strong assumption of PSM is that matched individuals have relatively similar unobserved characteristics and thus this problem is addressed. This has recently been shown not to be the case when an important part of the selection process relies on discretionary decisions.[§] As we have discussed this appears to be the case for HDC participation and although we will estimate the three described models, we do not want to conclude on the strength of a policy impact based on these. We therefore consider another methodology which should better address the discussed selection problem.

2) Regression Discontinuity Design

Regression Discontinuity Design (RDD) has had a long history in statistics, but has recently gained prominence among economists for its success in dealing with the problem of unobservable characteristics and its conceptual simplicity. This method can only be applied when there exists a cut-off point of an assignment variable *Z* above and below which there is a strong difference in treatment probability. As we clearly illustrate below, this is the case for HDC treatment depending on the length of sentence received (*Z)* due to the 3 months minimum selection rule.

A widely researched and very intuitive example of RDD occurs for the 50 percent cut-off rule for winning or losing an election. The argument is that different units (areas, firms) which have had very close votes around the cut-off are likely to be very similar observed and unobserved characteristics. Still they will have opposite outcomes whether they were above or below the assignment cut-off making it very simple to compare the difference in impact of selection or not. In this case, an unbiased treatment effect on outcome *Y* with subscripts + and – indicating proximity to either side of the threshold can be simply written as $\beta = Y^{+} - Y^{-}$.

It is extremely simple to estimate β here since being above the cut-off guarantees treatment and we only have to compare the means of the outcome around that point. This is called a *Sharp* RDD as the probability of treatment jumps from 0 to 1 on either side of the cut-off.

In the case of HDC treatment, as in many other programs, the change in the probability of treatment around the assignment variable threshold is not so sharp but does greatly increase. This type of set up is called a *Fuzzy* RDD and it is still possible to

[§] For a discussion on the strengths and weaknesses of PSM see for example Morgan and Harding (2006) exploit the discontinuity to identify a treatment effect. In this case however the difference in outcomes around the cut-off will be a function in the difference in the jump in the proportion treated around this point. Mathematically and using average recidivism, *Rec*, mean proportion released on electronic monitoring, *HDC*, and the subscript + and – as before, we can write $\mathrm{Re}c^{+} - \mathrm{Re}c^{-} = \beta(HDC^{+} - HDC^{-})$. This can be re-written as the RDD estimator:

$$\beta = \frac{\mathrm{Re}c^{+} - \mathrm{Re}c^{-}}{HDC^{+} - HDC^{-}} \tag{4}$$

If it is the case that offenders just below and just above the cut-off do have similar characteristics (observable and unobservable) then the estimator in equation (4) can legitimately be used to estimate the impact of HDC on recidivism. This is because it simply compares the difference in re-offending rates of individuals which have been randomly assigned around an assignment threshold and which should consequently have similar observed and unobserved characteristics. Of course since not all released prisoners above the 3 months cut-off are released on HDC, this must be scaled by the difference in the jump in the proportion that are treated around this point.

One important point for the validity of this method is that the discontinuity around the threshold only occurs in the treatment variable. That is we need to show that other variables which could impact on selection do not jump at this point, i.e. are continuous, and we will do this graphically. To be even more cautious with our results, we will also estimates the necessary differences in mean outcome and mean treatment around the cut-off controlling for observable characteristics and conducting PSM on the individuals released during this period.

3. Data and Descriptive Statistics

In this Section we discuss the data we use and show some descriptive characteristics for the individuals in our sample.

Data

We have drawn on data from the Local Inmate Database System (LIDS) which contains very detailed information on the sentence of every prisoner released offender in England and Wales between January 2000 and March 2007. These data contain more than 570,000 discharges for about 324,000 unique individuals due to multiple releases over this period. LIDS contains information on: sentence length; what crime offenders were sent to prison for; whether or not he/she was released on HDC, date discharged, date convicted. This data was matched, using the full name and date of birth of convicts, with a very high success rate (95 percent) to the Police National Computer (PNC). The resulting dataset contains information on arrests and convictions histories of all prisoners' pre and post release (in addition to all the sentencing details).

We have dropped individuals which had multiple discharges during this six year period because of computing and modelling complexity beyond the scope of this report. We also dropped all the individuals who were incarcerated for crimes which are statutory exclusion for eligibility to HDC such as sexual offences and breach of curfew orders. A difficulty arouse in matching the crime for which individuals were serving a sentence in the prison data among the multiple crimes recorded for these same individuals in the PNC. Using various dates (charged, sentenced, initial remand) available in this data, and windows of +/- 3 days to allow for imputing delay or error, we obtained a 94 percent match and were left with a sample of almost 280,000 discharges.

Because of the preferred methodology chosen to estimate the impact of HDC on recidivism, we then restricted the sample to twice the sentence length of 3 months or 88 days at which we have identified a cut-off point. This still therefore comprises of individuals with sentences inferior to 6 months or 180 days and represents very large 112,300 individuals or 40 percent of discharged prisoners in our sample. We are interested in measuring recidivism rate as our outcome variable of interest. We constructed a re-offending dummy which is equal to 0 if the prisoner does not have a crime recorded in the PNC 12 months after the end of his/her sentence and 1 otherwise.

Descriptive Statistics

Table 1 below shows a number of descriptive characteristics for prisoners in our sample, grouped by length of sentence and discharge type and reports their recidivism rates.

Table 1: Descriptive Statistics for Prisoners Released by Length of Sentence and HDC and Non HDC Discharges

Panel A - Released Before 3 Months:			
Discharge Type	**Non HDC**	**HDC**	**Total**
Percentage Female	12.2	-	12.2
Mean Age	29.5	-	29.5
Percentage Incarcerated for Violence	17.6	-	17.6
Mean Number Previous Offences	8.8	-	8.8
Recidivism within 12 Months	52.4	-	52.4
Sample Size	42,987	0	42,987
Panel B - Released Between 3 and 6 Months:			
Discharge Type	**Non HDC**	**HDC**	**Total**
Percentage Female	8.8	8.8	8.8
Mean Age at Release	27.6	30.8	28.4
Percentage Incarcerated for Violence	20.3	18.3	19.8
Mean Number Previous Offences	10	6.5	9.1
Recidivism within 12 Months	60	30.2	52.6
Sample Size	52,091	17,222	69,313

Panel A of the Table shows descriptive characteristics for prisoners discharged under 3 months and Panel B between 3 and 6 months. The first thing to note is that there are no observations for HDC discharge for earlier releases which is reassuring since they are not eligible for the scheme because of their sentence length. For the later releases in Panel B, 24.8 percent of individuals are released early on electronic tagging. The most striking difference between the HDC and non HDC discharges is the very large difference in number of previous offences and the difference in recidivism rate within a year of release. Prisoners discharged on HDC are almost twice less likely to re-offend. As this is our outcome of interest, we can assume that a simplistic model measuring the impact of HDC on recidivism is likely to generate very large estimates.

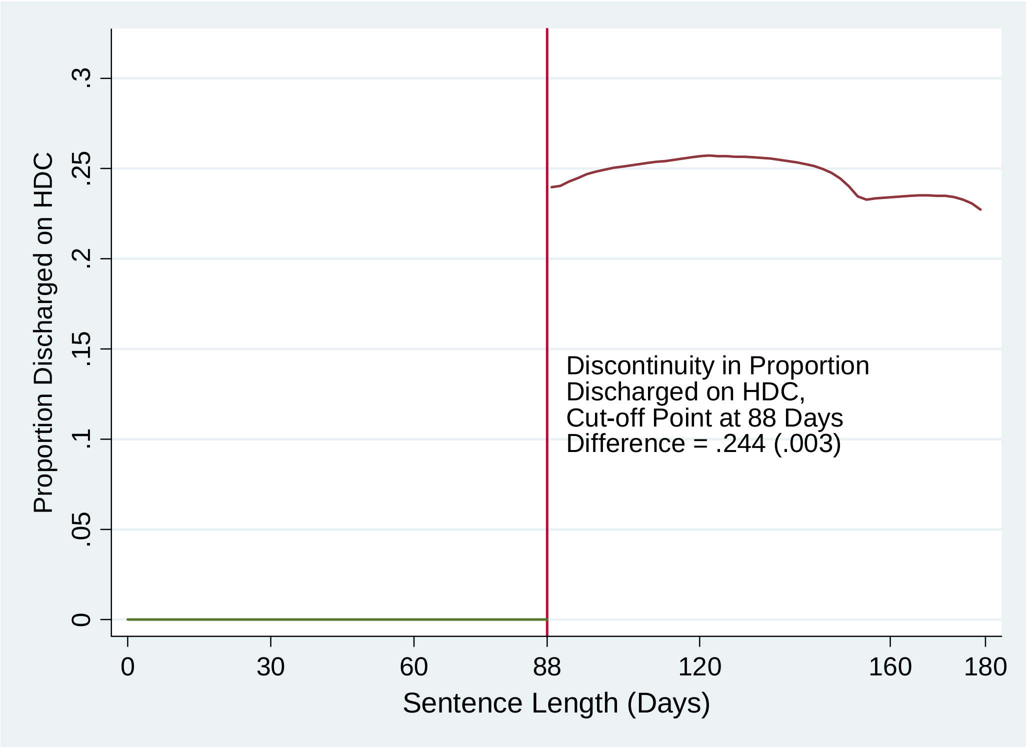
Table 2: Descriptive Statistics for Prisoners Released by Length of Sentence and HDC and Non HDC Discharges and +/-7 Days Around Discontinuity Threshold

Panel A - Released +/- 7 Days of 3 Months (88 Days) Cut-off:			
Discharge Type	**Non HDC**	**HDC**	**Total**
Percentage Female	10.5	9.7	10.3
Mean Age at Release	28.9	30.7	29.3
Percentage Incarcerated for Violence	19.8	18.2	19.4
Mean Number Previous Offences	9.5	5.7	8.7
Recidivism within 12 Months	54.6	28.1	48.8
Sample Size	18,928	5,351	24,279
Panel B - Released +/- 7 Days of 3 Months (88 Days) Cu-off:			
Day of Release around Cut-off	**- 7 Days**	**+ 7 Days**	**Total**
Percentage Female	11	10.2	10.3
Mean Age at Release	28.8	29.4	29.3
Percentage Incarcerated for Violence	17.1	19.7	19.4
Mean Number Previous Offences	9.1	8.6	8.7
Recidivism within 12 Months	56.8	47.9	48.8
Percentage Released on HDC	0	24.4	22
Sample Size	2,333	21,946	24,279

As we are interested in what occurs near the 88 days cut-off for eligibility, Table 2 shows descriptive characteristics for prisoners discharged a week before or a week after this duration. Again we note in Panel A that difference in number of previous offences and recidivism are very large between HDC and non HDC discharges. However we see in Panel B this difference is much smaller for those characteristics but there is a 24.4 difference in the proportion treated with HDC a week before and after the threshold. This is reassuring as it gives a first indication that on either side of the cut-off individuals have relatively similar observable characteristics, one of the assumptions of the RDD methodology. Although the sample size pre-threshold is much smaller than post-threshold, it is still much larger than what is used in most research implementing RDD thanks to the very large size of the data used.

As discussed above, we need to illustrate the discontinuity of HDC treatment graphically and also continuity of covariates which could influence the recidivism outcome. Figure 1 begins this by plotting the proportion of prisoners discharged on HDC with respect to the length of their sentence[**]. After the 88 time limit the jump of 24.4 percent jump afore mentioned in proportion treated is clearly visible and highly significant.

Figure 1: Proportion Discharged on HDC by Sentence Length



[**]All the graphs are local polynomials with a 7 day bandwidths to be comparable to our chosen window around the threshold for RDD estimations.

Figure 2: Mean Number of Previous Offence by Sentence Length

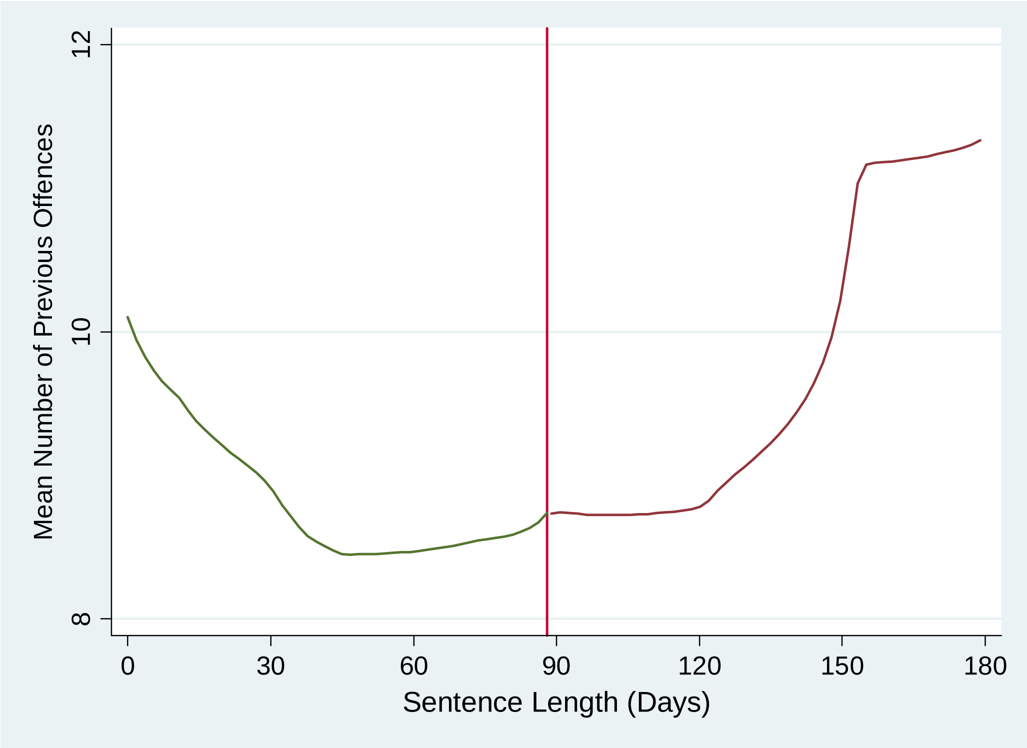


Figure 3: Mean Age at Discharge by Sentence Length

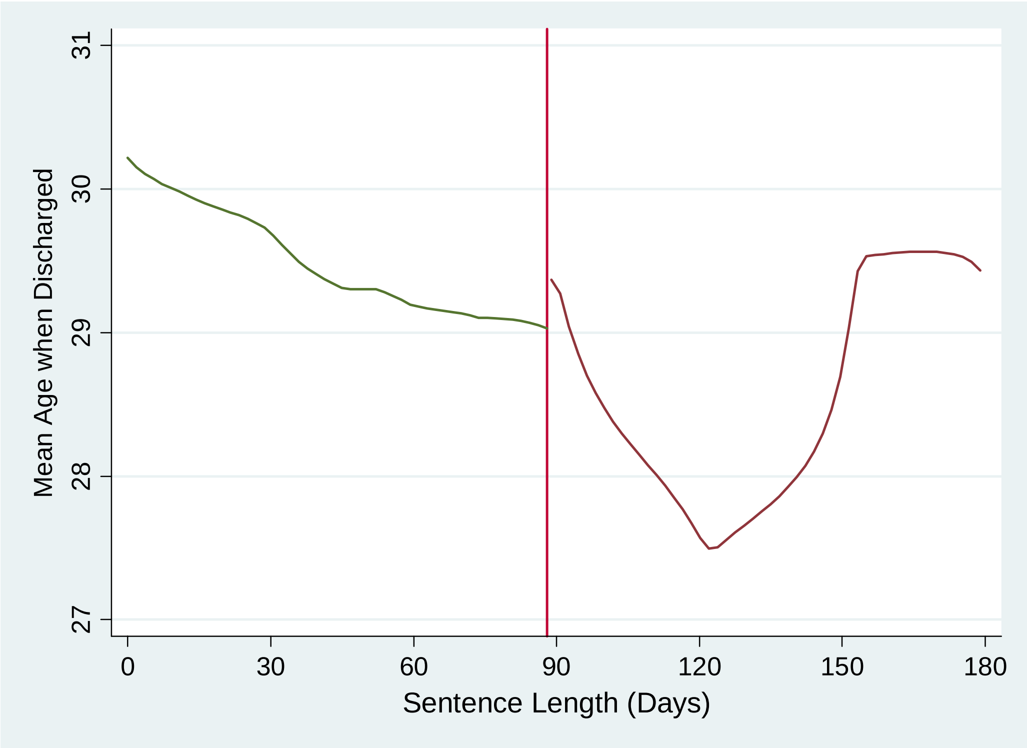
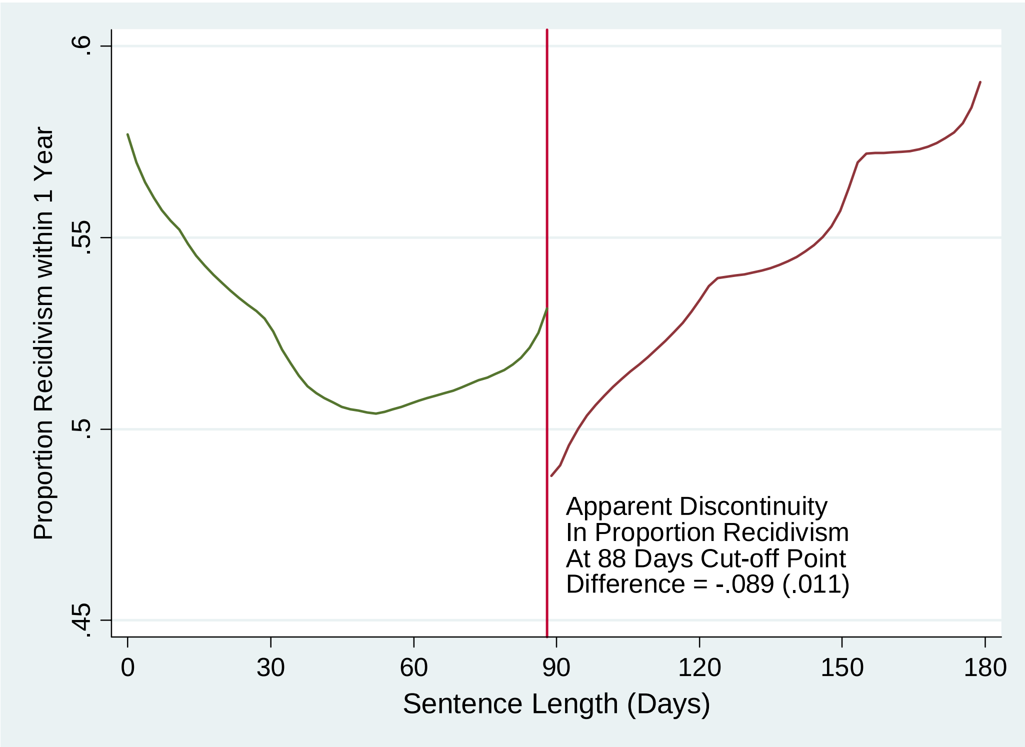


Figure 2 shows the mean number of previous offences by sentence length. Although the criminal history of prisoners is very different across the discharge period, the graph is very smooth around the HDC release threshold. This reinforces the validity of carrying out an RDD estimation of HDC as the number of previous offences could be strong selection criteria for scheme participation but is continuous around our assignment variable.

Figure 3 considers the mean age when released on sentence length. Again the graph is very continuous and the very small gap of the lines around the cut-off is not statistically significant. This again, as with Figure 2, points to a relatively random distribution of observable characteristics around the threshold which further validates the use of RDD.

Figure 4: Recidivism within 1 Year by Sentence Length



Finally, Figure 4 plots the rate of recidivism within 12 months of release by length of sentence. This graphical representation of the changes of our outcome variable of interests exhibits a striking jump around the 88 day threshold. This gap corresponds to a significant 8.9 percentage point lower re-offending rate of prisoners discharged one week after the cut-off compared to those one week before. As the only important difference we have observed so far between these two groups is the proportion discharged on HDC, we can say that, just from these graphs, the scheme appears to have a positive impact on recidivism. However, to formally assess if this is the case, we need to consider results from our statistical analysis and we turn to this in the next Section of the report.

4. Statistical Results

In this section I show estimates of the relationship between HDC participation and recidivism using the various methodological approaches we have already discussed. We first discuss estimates from the simple OLS and OLS with PSM using the whole 6 months sample and follow this with discussion of the RDD estimates using the +/- 7 days sample around the 88 days cut-off. This will enable us to contrast the difference in results obtained considering that the latter methodology should generate more reliable estimates. We then put the estimated impact of the scheme in perspective and briefly discuss them from a policy point of view.

OLS and OLS with PSM Results

We start by estimating equation (1) which is a raw effect of HDC on recidivism not controlling for any characteristics of prisoners selected into the scheme. We then augment the model as in equation (2) and control for a number of prisoner characteristics. These are: length of sentence in days, gender, age at release, number of previous offences, type of crime incarcerated for (burglary, drug offences, fraud and forgery, robbery, theft and handling, violence against the person, other offences, and offence not recorded), and month and year of discharge dummies.

The results are given in columns (1) and (2) of Table 3 for 112,300 discharged prisoners. The raw estimate without controls (column (1)) is very large and significant and represents almost a 30 percent lower recidivism rate for individuals who were discharged on HDC. This is certainly an over-estimate of the scheme impact as it does not take into account that eligibility for HDC which partly depends on being a low re-offending risk prisoner. The covariates we include as controls (column (2)) are likely to affect re-offending it is not therefore surprising to find that the estimated impact of HDC is now much smaller. It remains large and significant with early release on electronic tagging reducing the chance of re-offending by more than 18 percent. Again this is potentially a biased estimate of policy impact as it cannot control for unobservable which are correlated to HDC selection.

Table 3: OLS Estimates of Impact of HDC on Recidivism – Full Sample

	Dependent Variable = Recidivism Within 12 Months Estimation on Individuals Discharged Between 0 and 180 Days		
	(1)	**(2)**	**(3)**
HDC Discharge Dummy	-.293 (.004)	-.182 (.004)	-.193 (.006)
Day Discharged	Yes	Yes	Yes
Controls	No	Yes	Yes
PSM	No	No	Yes
Sample Size	112,300	112,300	112,300

Note: Robust standard errors in parenthesis. The controls included in column (2) are: length of sentence in days, gender, age, number of previous offences, month and year of release dummies, and the type of crime incarcerated for (8 types). The propensity score matching is based on the probit regression reported in Table A1 of the Appendix.

PSM generates a probability of policy participation on individual characteristics. We do this for HDC selection using the probit Pr[HDC = 1] on the controls used to estimate equation (2) above and the results from this probit regression are reported in Table A1 of the Appendix. The resulting propensity score assigned to each released prisoner allows us to match the HDC discharged ones to non-HDC discharged with the nearest score. We then re-estimate the OLS with controls and the report the result in column (3) of Table 3 above. We find that HDC still reduces recidivism probability by more than 19 percent. This is very consistent with the last estimate only controlling for prisoner characteristics but as we have already argued it could still be biased if the unobserved characteristics PSM cannot account for play an important part in HDC participation. We therefore now turn to the RDD methodology to obtain impact estimates which do not suffer from this problem

RDD Results

Because of the rule which imposes that prisoners sentenced to less than 89 days are not eligible to HDC we are able to consider RDD to investigate the impact of the policy on recidivism. The main argument for using this method is that since the cut-off is arbitrary, it is very likely that prisoners are randomly distributed on either side of it. We have shown graphically that there is indeed a strong discontinuity in the proportion of prisoners discharged on HDC around the 89 days threshold. There are 24.3 percent more HDC discharged in the week after compared to the week before the cut-off. We have also shown that two characteristics of prisoners, age and previous offences, which could impact on recidivism are continuous at this point. We finally saw that there is however a discontinuity in the outcome variable, re-offending, which we measured to be 8.9 percent lower for those released a week after the cut-off to those releases a week before.

If everyone was discharged on HDC after 88 days then we would have a Sharp RDD and the estimated impact of the policy would simply be this 8.9 percent estimate. However since the increase is only of 24.3 percent we must accordingly scale the measure of the policy impact. The results from this exercise are reported in column (1) of Table 4 below. The estimated effect is as in equation (4) the difference in mean outcome, -.089, divided by the difference in proportion treated, .243, around the threshold. The resulting estimate is a very large and significant[††] 36.6 decrease in recidivism due to HDC participation.

This estimate suggests that the policy indeed reduces recidivism. We can try and improve the average treatment effect measured by controlling for the observable characteristics of prisoners discharged around the threshold. The argument here is that even if they are randomly distributed on either side of the 88 days cut-off, it is still worth maximising the wealth of the data we have and control for prisoner characteristics which may affect HDC treatment and/or recidivism probability. The control variables used are the same as in the OLS models except that now we do not control for length of sentence due to the very small release window we are now using. Column (2) of Table 4 shows the results from this exercise and we now find that the scheme reduces recidivism by about 27 percent. Note here that both the difference in HDC participation, .233, and the difference in recidivism, -.059, around the threshold decrease.

[††] As the estimate is similar to a local IV estimate of recidivism on HDC instrumented by being discharged after the cut-off, we are able to obtain standard errors.

Table 4: RDD Estimates of HDC Impact on Recidivism – Around Threshold

	Dependent Variable = Recidivism Within 12 Months **Estimation on Individuals Discharged +/- 7 Days of 88 Days Threshold**		
	(1)	(2)	(3)
Estimated Discontinuity of HDC Participation at Threshold ($HDC^{+} – HDC^{-}$)	.243 (.009)	.223 (.009)	.243 (.003)
Estimated Difference in Recidivism Around Threshold ($Rec^{+} – Rec^{-}$)	-.089 (.011)	-.059 (.009)	-.044 (.014)
Estimated Effect of HDC on Recidivism Participation ($Rec^{+} – Rec^{-}$)/ ($HDC^{+} – HDC^{-}$)	-.366 (.044)	-.268 (.044)	-.181 (n.a.)
Controls	No	Yes	No
PSM	No	No	Yes
Sample Size	24,279	24,279	24,279

Note: Robust standard errors in parenthesis. The estimation is based on individuals released between 89 and 180 days. The controls included in column (2) are: gender, age, number previous offences, month and year of release dummies, and the type of crime incarcerated for (8 types). The propensity score matching in column (3) is based on calculating propensity scores for each individual using the same variables as the controls in the previous model.

Since controlling for observable characteristics does affect our estimate, we can go further and implement mix both PSM and RDD methodologies to obtain even more robust policy estimators. This is what we do in column (3) of Table 4. The main change now is that the difference in recidivism rates between prisoners discharged pre and post cut-off is significantly smaller at -4.4 percent. Consequently we can calculate that HDC participation reduces recidivism by about 18 percent[‡‡]. This is very close to our preferred estimated impact from the OLS with PSM above and we therefore conclude that being released early on electronic monitoring from prison appears to reduce recidivism probability by between 18 and 19 percentage points.

[‡‡] This is to our knowledge the first time that PSM and RDD have been combined to estimate a causal effect and there is therefore no simple methodology to obtain standard errors for this estimate. The reason is that we are not able here to run a local IV as before to generate the standard error. We however believe that the .181 coefficient is significant in view of the .044 standard errors in columns (1) and (2) and are working on a way to compute it precisely in the near future.

5. Conclusions

The most reliable results from our evaluation of the impact of the HDC scheme on re-offending, based upon a regression discontinuity design, produce evidence that HDC participants were less likely to engage in re-offending behaviour than otherwise similar non-HDC participants. In fact we observe a sizable, statistically significant, almost 20 percent reduction in the probability of re-offending in year following release. We would view this as tentative evidence that one early release programme, HDC, seems to have been able to generate crime reduction effects.

One should be still be careful not to conclude that extending the scheme to all prisoners discharged will have a similar impact on recidivism. We have estimated an average treatment effect and HDC may not have the same effect on the behaviour of the 70 to 75 percent of prisoners not released on the scheme. More cautiously we could however say with more certainty that it should reduce changes of re-offending by about the impact we have estimated for prisoners serving sentences less than 3 months if HDC became available to them.

Of course, the comparison is only with other offenders and so one needs to be careful to observe that the early release could still have crime increasing consequences relative to keeping offenders in prison, see for the discussion of issues to do with early release in the US in Austin (1986). At the same time it could, by reducing overcrowding, potentially decrease the chances of re-offending after release of prisoners released later. This issue of the dynamics of recidivism is a very interesting area of research which has not received the attention it deserves. We therefore view our results as encouraging in the sense that, with a rigorous research approach, we can pin down a significant reduction in the probability of re-offending.

A natural question to ask about is the mechanism by which recidivism fell for HDC participants relative to their non-participating peers. One could suggest that it is because of the reduced amount of time spent in prison thanks to the scheme or that curfew orders are a form of 'contract' with the released prisoner positive for re-insertion into society. Still out large scale quantitative analysis, by its very nature, remains silent on this but it would seem necessary that future work of a more qualitative nature will need to probe this in more detail so as to better understand how a scheme like HDC is able to reduce recidivism amongst offenders.

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Appendix

Table A1: Probit Models of HDC Participation as a Function of Prisoner Observed Characteristics

	Pr[HDC = 1]
	Prisoner Observed Characteristics
Length of Sentence	.016 (.000)
Gender	.015 (.021)
Age	.021 (.001)
Number of Previous Offences	-.044 (.001)
Committed Burglary	.297 (.225)
Committed Drug Offence	.989 (.226)
Committed Fraud & Forgery	.713 (.225)
Committed Robbery	-.204 (.243)
Committed Theft & Handling	.469 (.224)
Committed Violence Against the Person	.611 (.224)
Committed Other Offences	1.12 (.228)
Month of Release Dummies	Yes
Year of Release Dummies	Yes
Sample size	112,300

Notes: Marginal effects reported, standard errors in parentheses.