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Abstract

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1 Introduction

Parole—the conditional early release of prisoners—allows incarcerated offenders to complete the last portion of their sentence in the community. Because the sentence is still undergoing, parole allows exerting influence on parolees’ reintegration into their social and economic lives. However, parole’s net social benefits are unclear. On the one hand, it reduces the incapacitation time, which may increase recidivism. On the other hand, parolees’ supervision could prevent recidivism by ensuring an adequate transition from incarceration to life in society. Importantly, even if parole has a null effect on recidivism, the social benefits of lowering prison overcrowding and incarceration costs may still prove significant, such that identifying parole practices that do not generate recidivism could yield substantial social benefits. Unfortunately, although there is increasing convincing evidence that parole can decrease recidivism ([Kuziemko, 2013](#); [Macdonald, 2020](#); [Zapryanova, 2020](#); [Meier et al., 2020](#)), our knowledge of the contexts in which it is appropriate, or of the release practices that drive its success, remains extremely limited.

This paper studies the effect of parole in the particular context of the provincial prisons in Quebec, Canada, where parole is only granted to a narrowly selected group and where parolees are typically provided with comprehensive assistance facilitating their reintegration into society. We exploit the varying propensities of parole board members (PBMs) to grant parole as well as the as-good-as-random allocation of PBMs to prisoners’ parole hearings to estimate the causal effects of parole on recidivism and incarceration time. Using a novel methodology, we explore the role of halfway houses, where 75% of parolees are required to stay, in driving parole’s success. We consider the PBMs’ propensities to require a stay in a halfway house, combined with halfway houses’ fluctuating availability across time and space, to estimate the effect of a stay in a halfway house for two types of compliers: those at the margin of incarceration and those at the margin of release without a halfway house requirement.

We find that parole decreases recidivism by more than 8 percentage points within five years. It successfully decreases the total length of incarceration for compliers by about four months within five years while reducing the likelihood of committing further crimes. Halfway houses are especially effective at reducing recidivism for convicts at the margin of incarceration, thus suggesting that the broad assistance provided in these institutions, combined with an early release, plays a major role in desisting former inmates from crime.

Our data cover all sentences in the provincial prisons in Quebec from 2007 to 2021 as well as parole hearings from 2007 to 2015. Provincial prisons host offenders sentenced for less than two years, while those sentenced with at least two years go to federal prisons. However, in Quebec,

only inmates sentenced for more than six months are eligible to parole. Thus our analysis focuses on offenders with sentences ranging from six months to two years. The parole hearing takes place once the third of the sentence has elapsed unless the offender renounces to the hearing. In Quebec, the PBMs only choose whether they grant parole, and the attached conditions. They do not decide on the duration or timing of the early release. When parole is granted, the offender leaves prison just after the hearing and is subject to parole conditions from the third of the sentence to its original term. When parole is denied, the inmate is released normally, without conditions, usually after serving two-thirds of the sentence. The reason being that two days of good behavior behind bars reduces the incarceration time by one day, a rule that does not apply to parolees. Thus, our approach effectively compares inmates who are granted a release at the third of their sentence and who are provided with substantial rehabilitation assistance to their counterfactuals: incarcerated inmates released at the two-thirds without said assistance. Note that prisoners may still receive rehabilitation assistance while incarcerated by participating in social rehabilitation programs.¹ However, parolees in halfway houses receive more personalized, continuous and longer-term assistance that is specifically aimed at ensuring a proper transition.

Hearings are held online, allowing PBMs to be assigned to any hearing regardless of the prisoner’s location. Discussions with Quebec Parole Board members revealed that they are assigned to hearings mostly based on availability and in a manner to distribute the workload evenly during the week. The prisoner’s characteristics not being taken into account suggests that a prisoner’s assignment to a PBM is as good as random. This setting allows for a typical “judge” (in our case PBM) fixed-effect design.² Following the literature, we construct an instrumental variable that measures the assigned PBM’s propensity to grant parole, and show that this instrument does not correlate with inmates’ characteristics but shifts their likelihood of being granted parole. Our 2SLS results show that parole decreases recidivism by about 8 percentage points within five years following the hearing. The shorter term effects are still negative though not statistically significant, possibly because parolees have more time to recidivate, which could counterbalance the effect. Overall, these results suggest that parole decreases recidivism in a context where compliers are relatively low-risk. We explore heterogeneity in the results and find that lowest-risk offenders indeed benefit the most from parole.

We next study the effect of parole on time spent in prison. In our setting, parolees see

¹See [Arbour \(2021\)](#) and [Arbour et al. \(2021\)](#) for evidence that such programs can decrease recidivism in our context.

²See, for instance, [Kling \(2006\)](#); [Loeffler \(2013\)](#); [Aizer and Doyle Jr \(2015\)](#); [Mueller-Smith \(2015\)](#); [Leslie and Pope \(2017\)](#); [Dobbie et al. \(2018\)](#); [Stevenson \(2018\)](#); [Bhuller et al. \(2020\)](#); [Arteaga \(2020\)](#); [Norris et al. \(2020\)](#); [Agan et al. \(2021\)](#); [Eren and Mocan \(2021\)](#).

their incarceration time mechanically imputed by one-third of their sentence duration. Hence, parole could help decrease incarceration costs and help relieving prison overcrowding even if it had no effect on recidivism. Using our instrumental variable strategy, we estimate that parole causes inmates to spend 117 fewer days in prison within five years following the hearing. This effect is primarily driven by the direct mechanical effect of releasing inmates earlier (-119 days incarcerated). It is partly counterbalanced by parolees who are found to commit a technical violation of parole conditions, for whom parole is revoked. These individuals return to prison to finish their sentence, increasing incarceration time by 28 days on average for compliers. Thus, the net release effect of parole is a reduction of 91 days (-119+28) incarcerated for the current sentence. Looking at future sentences following new crimes, we find that parole decreases incarceration length by 27 days. Therefore, the estimated overall causal effect of parole in our setting is a reduction of around 117 days of incarceration time.

We explore the role of halfway houses in the rehabilitation process. Halfway houses in Quebec cover basic necessities such as shelter, food and beds, as well as extensive rehabilitation assistance. In addition to specific therapies and programs, parolees in halfway houses can obtain help in finding a job, learn how to cook and buy groceries, and be guided through the process of obtaining a driver's license or a health insurance card. To provide these services, practitioners at halfway houses must have a professional degree in criminology, psychology, social work, counseling or psychoeducation. Staying in a halfway house is not random. Before the hearing, the inmate must work with their designated prison officer to develop a rehabilitation plan. As part of the plan, the prison officer can directly contact halfway houses managers to inquire if they are willing to house the inmate in case he is granted parole. Importantly, halfway houses can be constrained in how many parolees they can accept due to financial and staffing fluctuations, and a fixed number of beds. During the hearing, the PBM is aware of whether the candidate intends to go to a halfway house and whether he has been accepted; however, the ultimate decision lies with the PBM. In Quebec, almost 3/4 of parolees are required to stay in a halfway house. Offenders at the margin of remaining incarcerated will almost certainly be subjected to this stringent condition. It is thus conceivable that the practices in these halfway houses are part of the mechanism underlying our positive rehabilitation results.

To generate exogenous variations in the likelihood of staying in a halfway house, we create an instrument that exploits both the varying availability of halfway houses across time and regions, and the PBMs' propensities to send offenders in halfway houses. With our two instruments in hand—one to predict whether parole is granted without a halfway house requirement and a

second for halfway houses being required—we adapt [Mountjoy \(2021\)](#)’s novel methodology to estimate the effect of halfway houses for two types of compliers. Firstly, we estimate the effect of staying in a halfway house for offenders at the margin of remaining incarcerated. For this group of compliers, we find a negative effect on recidivism of around 12 percentage points, indicating that being released with extensive rehabilitation assistance significantly prevents recidivism. Secondly, we estimate the effect of being sent in a halfway house for those at the margin of being granted parole *without* the halfway house requirement. For this group, the estimated effects are too imprecise to draw any conclusion.

Contribution to the literature

This paper first contributes to the literature seeking to understand the causal effect of parole on recidivism or other outcomes. Many papers, while not studying parole, estimate the effects of incarceration length, which is one aspect of parole.³ Parole, however, is more than just a reduction of incarceration length, as it may come with supervision or rehabilitation assistance. Some papers, more related to ours, exploit reforms that limited the possibility of obtaining parole for some offenders. [Kuziemko \(2013\)](#) studies such a reform in Georgia and finds a significant increase in recidivism caused by the reform. Exploring the underlying mechanism, she provides evidence that the effect is in part driven by the lower incentives to exert rehabilitation efforts which resulted in a decline in prison programming participation. [Macdonald \(2020\)](#) studies a reform in Arizona eliminating the possibility of an early release. He finds similar results and shows that violent offenders are most impacted. These studies report the cumulative effect of an increase in time served and of reduced programming participation. Few studies identify the direct effect of parole, and their results are mixed. On the one hand, [Zapryanova \(2020\)](#) relies on guidelines provided to the Georgia Parole Board to disentangle the effects of time spent in prison and time spent on parole on reincarceration upon release and finds that parole has no significant effect. On the other hand, [Meier et al. \(2020\)](#) leverage variation in Israeli judges’ leniency during a day to find that one month spent outside of prison reduces the probability to recidivate by 8 percentage points. Our paper is close to [LaForest \(2022\)](#), who also uses a parole board member fixed effect design to estimate the effect of parole in Pennsylvania. He finds no effect on new crimes after release. However, he finds that parole increases rearrests within one year after release, though this increase is not related to new crimes but rather to

³See, for example, [Kling \(2006\)](#); [Jung \(2011\)](#); [Landersø \(2015\)](#); [Bhuller et al. \(2020\)](#); [Mukherjee \(2021\)](#) and [Rose and Shem-Tov \(2021\)](#).

technical violations of parole conditions.

Many factors could account for these mixed results. Parole is likely to be appropriate for some offenders but not for others, and its success could depend on the specific parole policies and practices. Thus, it is essential to conduct additional studies estimating the effect of parole for different populations of compliers to understand *who* should be granted parole, and *how* it should be granted. Our paper contributes to this literature and highlights that parole is successful for our relatively low-risk compliers—even more so for the lowest-risk offenders among this group. This could explain why our results differ from [LaForest \(2022\)](#). In his setting, most offenders are granted parole, while, in ours, only a narrowly selected group of around 23% of eligible offenders obtain it. What is more, we study a context where substantial rehabilitation assistance is provided to parolees, which is likely to influence the causal effect of parole.

Our paper also relates to the literature relating supervision of ex-offenders and reincarceration. Because parolees are placed under stringent supervision, a supervised transition could increase reincarceration in the short term because of technical violations. Significant attention has been given to electronic monitoring as a substitute for detention and it has consistently been found to decrease recidivism ([Henneguelle et al., 2016](#); [Williams and Weatherburn, 2019](#); [Di Tella and Schargrofsky, 2013](#)). In contrast, such supervision is found to be ineffective after a prison spell—either under probation or parole—by a large number of studies.⁴ [LaForest \(2022\)](#) shows that the level of parole supervision in Pennsylvania is related to rearrests resulting from technical violations: lowest and highest supervision levels are associated with higher probabilities of rearrest in his setting. Close to our paper, [Lee \(2022\)](#) observes that parole case workers in Iowa vary in their propensity to recommend residential housing to parolees. Using these propensities as an instrument, he shows that parolees in halfway houses recidivate more and faster than their counterparts at home, and that returns to incarceration are driven by technical violations. This suggests that a higher degree of supervision under parole might prove counterproductive if parolees in halfway houses spend more time incarcerated after their initial release. Our paper provides insights complimentary to [Lee \(2022\)](#). First, we show that halfway houses are beneficial compared to remaining incarcerated, while [Lee \(2022\)](#) finds they increase reincarceration compared to being released without a requirement to stay in a halfway house.⁵ We point out that, in our context, reincarceration time from technical violations counterbalances only to a small extent the substantial reduction of incarceration time directly caused

⁴See for instance [Hyatt and Barnes \(2017\)](#) and the references therein.

⁵As mentioned above, we also estimate the effect of going to a halfway house for individuals at the margin of being released without a requirement to stay in a halfway house. However, our results are too imprecise to draw any conclusion.

by parole. Second, we highlight that halfway houses in our context are substantially oriented toward rehabilitation, which could explain their beneficial impacts.

Although stringent parole supervision could raise the rate of reincarceration, it can also help offenders if it is combined with rehabilitation assistance. The last portion of the paper studies the role of halfway houses, where inmates receive specialized therapy, job counselling and all-around services. Such services could prove beneficial as often-cited barriers to rehabilitation include treatment retention (Hall et al., 2017) and navigating a difficult job market (Yang, 2017; Schnepel, 2018; Agan and Starr, 2017). In many ways, halfway houses in Quebec are similar to open prisons in Europe. Mastrobuoni and Terlizzese (2022) leverage exogenous variations between *closed* and an *open* prison in Italy, where inmates can move freely between the prison’s walls, undertake therapy, take classes and, for a subset of inmates, work during the day. The authors find that one year in an open prison significantly reduces recidivism. This suggests that punitive-oriented prisons may depreciate inmates’ human capital and prove criminogenic. Our paper adds to this literature by showing that parole decreases recidivism especially for those moving into halfway houses, where parolees can move in and out, and are provided with substantial rehabilitation assistance.

Our last contribution is to integrate the novel methodology proposed by Mountjoy (2021) to the well-established judge fixed-effects design framework. This allows us to estimate the effect of halfway houses for different groups of compliers. This could be applied to other settings, since *judges*—or examiners—usually make multiple decisions regarding one case. Another approach is Arteaga (2020), who develops an econometric framework dealing with judges deciding on whether an individual is convicted *and* incarcerated to isolate the effect of parental incarceration on children’s outcome. Our methodology departs from this framework by estimating the effect of halfway houses for different types of compliers.

The rest of the paper unfolds as follows. Section 2 discusses the institutional features of the Quebec parole process. The data and descriptive statistics are presented in Section 3. In Section 4, we apply our instrumental variable strategy to measure to causal effect of parole on recidivism and incarceration, and we estimate the effect of an early release in a halfway house for two types of compliers. Section 5 concludes.

2 Institutional Details

The provincial prisons in Quebec house inmates who serve sentences ranging from one day to two years. Inmates receive a one-day sentence reduction for every two days of good behavior while incarcerated. As a result, they are usually released without conditions after serving two-thirds of their sentence. One exception prevails. Inmates who serve sentences of at least six months are eligible for parole starting at the third of their term. The parole board will meet with every eligible candidate at the third of their sentence unless the inmate waives this right in writing. If an inmate renounces to parole, they are released at the two-thirds of their sentence as planned.

About 50% of eligible offenders renounce to parole. On the one hand, if parole is granted, the board’s parole terms extend up to “three-thirds” of the sentence—the original sentence ending date. When prisoners, on the other hand, forgo their right to parole and choose to stay incarcerated, they are freed without conditions. The process is depicted on Figure 1. If a parole condition is violated and reported by the parole officer in charge of the case, the parolee returns to detention and remains incarcerated for the two-thirds of the residual sentence length.

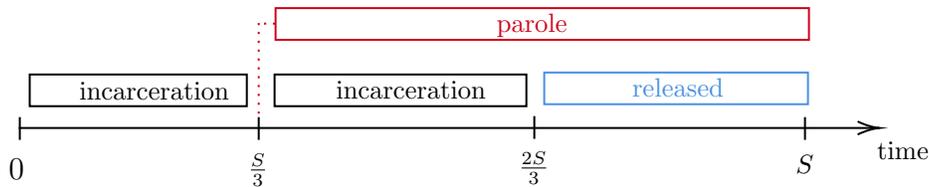


Figure 1: Timeline of a Prison-Parole Spell

Notes: This figure illustrates the timeline of the incarceration and parole processes in Quebec. At the one-third of the initial sentence length S , the offender may either be released under parole and be subject to parole conditions until S , or remain incarcerated until $2S/3$, after which no condition applies.

When an offenders seeks an hearing, the parole board’s clerk independently assigns the case to a parole board member in a way to balance the weekly workload among the commissioners. At any given time, the parole board consists of approximately 20 PBMs, half of whom work full-time as commissioners while the other half only evaluates cases during busier weeks. PBMs are trained to broadly assess all potential cases, from the lightest to the most serious. Nevertheless, a very small fraction of PBMs are specialized to handle the cases of Native inmates, who represent a significant proportion of the Quebec’s prison population. The PBMs typically have acquired several years of experience on the field or within the criminal justice system before being appointed to the board. As such, most hold a law, a criminology or a social work degree.

The government appoints full-time members for terms of up to five years.

In the earlier years of our analysis, the PBMs would cover the entire Quebec territory for in-person hearings. Yet, to make the schedules manageable, PBMs would be assigned to specific regions and would most cover the cases from two to five prisons. Progressively, hearings have transitioned to videoconferencing, thus removing any geographical ties between PBMs and prisons. Our analysis will account for geographical ties in the earlier years. PBMs can be joined at hearings by appointed community members to ensure that the PBM is familiar with the community services available in the region where the parolee would be released. In some cases, two PBMs can be assigned to an hearing—namely when the candidate is a violent offender or sentenced for domestic abuse.⁶

During the hearing, the candidate seeking parole meets the parole board member, who has reviewed the case before the hearing. In particular, PBMs have access to the correctional files—including, for instance, the record of program participation, disciplinary notices and criminal history—and the risk evaluation performed at the sentence’s onset. They further review the inmate’s release plan, usually devised in coordination with a prison officer. During the hearing, the PBM will assess the likelihood of reintegration by reviewing the file along with the candidate. They ask detailed questions about the crime committed and its causes, their criminogenic needs, and their entourage’s involvement in criminal activities. Family members and employers can demonstrate their support by sending written letters to the board. In addition, the candidate can be joined by family members and their legal counsel during the hearing. Following the hearing, the appointed commissioner deliberates and decides on whether or not to grant parole, as well as on the conditions to impose. They normally notify the inmate of their decision within a day. Around 46% of those who do not renounce to their hearing are granted parole. Therefore within the whole sample of eligible offenders (within which 50% renounce to the hearing), around 23% of inmates obtain parole.

If parole is granted, the commissioner issues a certificate outlining the conditions that will have to be respected while on parole. This certificate is usually issued within a day; importantly, PBMs do not choose the date at which parole begins nor how long it lasts. As mentioned before, the parole period, if granted, starts at the third of the sentence up to the total sentence’s term. All parolees are subject to a bundle of seven standard conditions, which include the requirement to actively exert effort towards their rehabilitation, refrain from using alcohol and intoxicating substances, and avoid being in the presence of criminals. The PBM can specify

⁶A second instrumental variable for a second PBM only weakly correlates with the decision and leaves the results unchanged. The results are available upon request.

other conditions based on the parolee's criminogenic needs. In the case of a technical violation, the parole officer—not the PBM—files a report and parole is revoked as the offender returns in detention. After the hearing, the PBM does not interact with the offender nor do they follow-up on the case. A standard parole certificate indicates between 15 and 20 conditions, including, for instance, looking for a legitimate job, residing at a specified address or actively participating in therapy. One salient condition is staying in a transitory halfway house. When sent in a halfway house, the parolee stays there for the entire parole term.

There are about 70 halfway houses in Quebec, each accommodating anywhere between five and twenty residents. Halfway houses, as displayed on Figure 2, are usually comfortable environments with cooking facilities, single- or double-occupancy bedrooms and multi-purposes rooms for watching sport or TV shows. Halfway houses offer comprehensive services like mental health therapy and substance addiction treatment delivered by a range of professional counselors. Rehabilitation professionals assist parolees in preparing for reentry by guiding their search for permanent housing and employment, as well as honing their budgeting ability. Parolees get three meals a day and must respect strict curfews. Yet, during working hours, parolees in halfway houses are free to move in and out. It is worth noting that offenders who remain incarcerated may also obtain rehabilitation assistance through in-prison programming. [Arbour \(2021\)](#) and [Arbour et al. \(2021\)](#) use participation data from prisons in the same setting and find that such programs can decrease recidivism.



Figure 2: Pictures of Halfway Houses

Note: This figure presents publicly available pictures of halfway houses in Quebec taken from some of the halfway houses' websites.

3 Data and Descriptive Statistics

To carry-out our analysis, we combined the three following datasets provided by the Quebec's Ministry of Public Security:

Parole Hearings. We obtained access to the entire body of decisions from the parole board from 2007 to 2015. This dataset includes the unique identifiers of the parole candidate (allowing us to match the data with the other databases mentionned below) and of the appointed PBM. As a result, we can trace the history of PBMs' decision across time. If parole is granted, the list of imposed conditions is provided. Technical violations are also documented.

Correctional files. The correctional files follow inmates' trajectories within the criminal justice system through a unique identifier from 2007 to 2021. Each identifier is matched with demographic characteristics such as the gender, age at sentencing and the Native status. The data precisely records the crime committed. We categorize crimes into four broad categories: assault, burglary and theft, crimes related to drugs, and *other*.

Psychological assessments. Finally, the Level of Service/Case Management Inventory ([Andrews et al., 2000](#)) is used to assess inmates' needs and risk from the start of their sentence. The questionnaire—commonly known as the LS/CMI—comprises eight sections yielding to eight risk scores. Handled by a trained officer, the assessment primarily documents the criminal history

of the individual, their consumption of alcohol and drugs, and their educational attainment.

Table 1 summarizes the available variables. It include only offenders who had a parole hearing from 2007 to 2015, thus excluding those not eligible (i.e. sentences of less than six month) and those who renounced to their hearing. We divide our sample into three groups: 1) those whose parole is denied; 2) those whose parole is granted with a halfway house stay requirement, and 3) those whose parole is granted without a halfway house stay. The risk scores (RS) are higher in the *denied* group. As expected, the *halfway* and *no halfway* groups are drastically different, with the former systematically comprising of higher-risk individuals. Inmates convicted for an assault are overrepresented in the *denied* group; in contrast, non-violent drug offenders are more likely to be granted parole.

Table 1: Descriptive Statistics by Parole Status

Parole Status	Denied		Granted—Halfway		Granted—No Halfway	
	Mean (a)	SD (b)	Mean (c)	SD (d)	Mean (e)	SD (f)
RS—Criminal History	6.011	1.695	5.004	2.112	3.346	2.170
RS—Education/Employment	5.356	2.658	4.762	2.680	2.693	2.480
RS—Family/Marital	1.983	1.125	1.648	1.156	1.085	1.043
RS—Procriminal Attitude	1.832	1.244	0.961	1.049	0.649	0.986
RS—Companions	2.705	0.974	2.404	1.000	1.815	0.921
RS—Leisure/Recreation	1.582	0.628	1.421	0.702	1.029	0.717
RS—Alcohol/Drugs	4.009	2.278	3.364	2.346	1.727	1.987
RS—Antisocial Pattern	1.939	1.118	1.338	1.087	0.638	0.869
Age	37.860	12.011	36.356	11.723	39.975	13.112
Number of Dependents	0.409	0.954	0.380	0.897	0.497	0.980
Crime: Other	0.211		0.181		0.228	
Crime: Assault	0.185		0.119		0.079	
Crime: Burglary and theft	0.292		0.255		0.101	
Crime: Drugs	0.313		0.445		0.592	
Indigenous	0.050		0.019		0.025	
Male	0.947		0.910		0.903	
Female	0.053		0.090		0.097	
Observations	5653		3449		1264	
Share of sample	0.545		0.333		0.122	

The first eight variables are risk scores (RS).

High risk scores are associated with a high risk of recidivism.

From the correctional files, we construct our main outcome of interest—recidivism. We define recidivism as another crime being committed following the current sentence. That is, we exclude technical violations of parole conditions, which cancel the offender’s parole status and

cause a return to incarceration. To deal with parolees having *more time* to recidivate when compared to those whose parole is denied, we consider recidivism starting at the date of the decision (at the third of the sentence) and we do so with varying time windows—between 1 and 5 years after the clock starts. Later in the analysis, we consider the incarceration length as the dependent variable, decomposing the effect in i) the direct release of paroles ii) technical violations leading to reincarceration, and iii) the effects on future sentences.

In our setting, selection may arise from two sources: 1) a self-selection effect stemming from prisoners choosing whether or not to seek parole and 2) a selection effect resulting from the PBM who grant or deny parole. The former mechanism is well apparent from Figure 3, where we measure recidivism rates for varying time frames. It shows that recidivism rates are significantly higher for those who renounce to their hearing, even when compared to those who were denied parole, hovering around 60% within five years after release. Parolees have significantly lower recidivism rates than those who are denied parole. This may arise from two effects: the PBMs' selection effect and the causal effect of parole. The PBMs' selection effect is likely negative: they seek to grant parole to those less at risk of recidivating. The direction of the causal effect is ambiguous: it may comprise rehabilitative effects of transitory assistance provided during parole, but also reduced incapacitation or desistance. We finally observe significant differences in rates between those released on parole with and without the requirement of staying in a halfway house. Again, the selection effect in this case likely goes in the direction of lower recidivism for those who are not imposed this condition, while the causal effect of halfway houses is ambiguous.

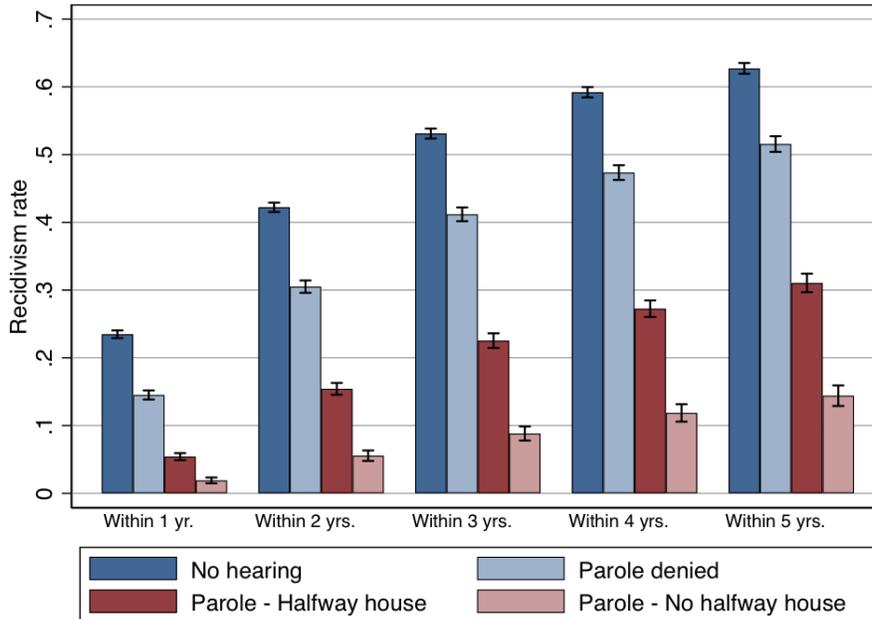


Figure 3: Recidivism rates

Notes: This figure presents the recidivism rates within different time spans after release. “No hearing” is the sample of prisoners who chose not to have an hearing requesting parole. “Parole denied” is the sample of prisoners who had an hearing but were denied parole. “Parole - Halfway house” and “Parole - No halfway house” are those who were granted parole, with and without the imposition of living in a halfway house respectively. 95% confidence intervals for proportions are shown.

4 Estimations and Results

4.1 Research Design

Parole is not random. Indeed, the PBMs responsible for rendering the decisions interact with the inmates and select those with the earnest motivation to rehabilitate and other positive traits unobserved in the data. The first column of Table 2 reports the results from an OLS regression of a parole dummy (0 if parole denied, 1 if granted) on the set of characteristics. The estimation excludes those who renounced to their hearing, as for the rest of our analysis. All the risk scores are negatively correlated with parole being granted, as is the crime being an assault. Those who committed drug-related crimes have more chances of being granted parole.

To disentangle the causal effect from the board’s selection, we construct a residualized PBM leniency measure. At this stage, we aim to estimate the causal effect of parole on recidivism regardless of whether parolees stay in halfway houses. To account for (i) PBMs being elected for up to five years, (ii) PBMs having some geographical ties in earlier years and (iii) some, although very few, PBMs being specialized cases of inmates from Indigenous backgrounds, we

Table 2: Randomization Test (OLS regressions)

	(1) Parole	(2) z^p
RS-Criminal History	-0.041*** (0.003)	0.000 (0.000)
RS-Education/Employment	-0.007*** (0.002)	-0.000 (0.000)
RS-Family/Marital	-0.008* (0.004)	0.000 (0.001)
RS-Procriminal Attitude	-0.103*** (0.004)	-0.001 (0.001)
RS-Companions	-0.002 (0.005)	0.000 (0.001)
RS-Leisure/Recreation	-0.015** (0.008)	0.002* (0.001)
RS-Alcohol/Drugs	-0.009*** (0.002)	0.000 (0.000)
RS-Antisocial Pattern	-0.004 (0.006)	-0.001 (0.001)
Age	-0.003*** (0.000)	-0.000 (0.000)
Crime: Assault	-0.054*** (0.015)	-0.001 (0.003)
Crime: Burglary and theft	0.002 (0.013)	-0.005** (0.002)
Crime: Drugs	0.066*** (0.012)	-0.002 (0.002)
Number of dependants=1	-0.020 (0.015)	-0.003 (0.003)
Number of dependants=2	-0.018 (0.017)	0.003 (0.003)
Number of dependants=3	0.008 (0.025)	-0.000 (0.005)
Number of dependants=4	0.020 (0.039)	-0.005 (0.008)
Number of dependants=5+	-0.133*** (0.044)	-0.013 (0.008)
Constant	1.022*** (0.023)	0.004 (0.004)
N	10366	10366
Controls	Year	Year
F-stat	216.25***	1.08

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Year Controls include year fixed effects

The F statistic tests the significance of the short regression

first regress the parole decision of inmate i , evaluated by PBM j , on year and prison fixed effects and a Native dummy:

$$\text{parole}_{ij} = \beta_0 + \beta_1 \text{year}_i + \beta_2 \text{prison}_i + \beta_3 \text{Native}_i + \epsilon_{ij}. \quad (1)$$

Let $\hat{\epsilon}_{ij}$ be the residual from this regression. PBM j has reviewed the cases contained in the set \mathcal{N}_j . For each PBM j , let $\tilde{\epsilon}_j = \sum_{i \in \mathcal{N}_j} \hat{\epsilon}_{ij}$. For an inmate i who meets with a PBM j , we define the instrument as

$$z_{ij}^p = \frac{\tilde{\epsilon}_j - \hat{\epsilon}_{ij}}{|\mathcal{N}_j| - 1}, \quad (2)$$

where $|\mathcal{N}_j|$ denotes the total number of cases reviewed by PBM j . Because of the controls included in Equation (1), z_{ij}^p can be interpreted as the relative leniency of the PBM who has met with inmate i on a given year in a given prison and given a specified Native status compared to all the other available PBMs.⁷

Intuitively, our design leverages exogenous variation resulting from the random assignment of PBMs to hearings: for instance, let the propensity of granting parole of PBM j be greater than that of PBM k . This implies $z_{ij}^p > z_{ik}^p$, such that inmate i is more likely to be granted parole if randomly assigned to PBM j . This instrument is commonly known as a leave-one out propensity, as it excludes inmate i when computing j 's average to remove small sample bias.

Our design exploits various 2SLS regressions of the form

$$\text{parole}_{ij} = \alpha_0 + \alpha_1 z_{ij}^p + \mathbf{x}'_i \boldsymbol{\delta} + \epsilon_{ij} \quad (\text{first stage}) \quad (3)$$

$$\text{recidivism}_{ij} = \beta_0 + \beta_1 \text{parole}_{ij} + \mathbf{x}'_i \boldsymbol{\beta} + \eta_i \quad (\text{second stage}) \quad (4)$$

where \mathbf{x}'_i contains, depending on the specification, up to all the variables listed in Table 1 plus year and prison fixed effects. We next discuss the properties of z_{ij}^p that allow for β_1 —the effect of parole of recidivism—to be interpreted causally and as a local average treatment effect (Angrist et al., 1996).

Random assignment. Extensive discussions with the Quebec parole board revealed that PBMs are randomly assigned to hearings, especially in the later years when online hearings removed any geographical ties between PBMs and prisons. As a result, conditional on the hearing's year and prison, and conditional on the Native status of the candidate, the assignment

⁷In practice, the Native dummy has no impact on our measure. Still, we include it to account for the institutional framework. Figure B.1 in the appendix shows the distribution of the non-leave-out (i.e., PBM specific) version of the instrument, keeping only one observation by PBM.

can be viewed as random. We formally test the random assignment by estimating a regression of the instrument on our full set of inmates’ characteristics. The results are reported in the second column of Table 2. These characteristics do not correlate with the instrument; that is, the characteristics do not predict the leniency of the assigned PBM. The non-significant F statistic of 1.08 further supports this argument.

First stage. The instrument z_{ij}^p must strongly correlate with i ’s likelihood of being granted parole. Columns (1) and (2) of Table A.1 report the estimates of the first stage regression (Equation 3). Our PBM leniency measure strongly predicts the parole decision irrespective of whether additional controls are included. The F statistics rule out the possibility of the instrument being weak (Olea and Pflueger, 2013).

Exclusion restriction. The assigned PBM must influence the inmate’s future outcomes through only their decision at the parole hearing. This assumption is unlikely to be violated in our setting. After the hearing, the PBM does not interact any further with the offender and does not follow-up on the case.

Monotonicity. We follow Bhuller et al. (2020) and estimate first stage regressions across different subsamples of our data and across the distribution of z^p . The estimates are reported in Table A.2 and Table A.3. All the coefficients are positive and significant. This indicates that the instrument strongly correlates with the parole decision for various types of inmates, and allows for interpreting the results as the causal effects of parole for the population of compliers.

4.2 Results

Table 3 first presents OLS estimates of the effect of parole as a benchmark. Estimations in Panel A include only year fixed effects as control variables. Parolees recidivate at a considerable lower rate than non-parolees both in the short and long runs. Five years after release, parolees have a recidivism rate 26 percentage points lower than that of non-parolees. In Panel B, we add the eight risk scores on which the PBMs may partially base their decision. The estimates shrink by more than half, thus suggesting that the risk scores pick up a large portion of the selection effect. In Panel C, we control for all the inmates’ observed characteristics and add prison fixed effects. Between Panel B and C, the coefficients barely change: we estimate a difference between 4 and 8 percentage points in the recidivism rates of parolees and non-parolees. These estimates represent decreases of between 38% and 19% of the baseline recidivism rates.

The results from the 2SLS regressions are shown in Table 4. As for the OLS regressions, Panel A includes only year fixed effects as control variables, Panel B adds the risk scores, and

Table 3: OLS estimation

<i>Recidivism within...</i>	(1) 1 Year	(2) 2 Years	(3) 3 Years	(4) 4 Years	(5) 5 Years
Panel A: Year Controls					
Parole granted	-0.108*** (0.008) [-0.123,-0.092]	-0.184*** (0.015) [-0.213,-0.156]	-0.226*** (0.022) [-0.268,-0.183]	-0.249*** (0.025) [-0.297,-0.200]	-0.255*** (0.024) [-0.302,-0.208]
Observations	10366	10366	10366	10366	10313
Panel B: Year + Risk Scores Controls					
Parole granted	-0.051*** (0.006) [-0.062,-0.040]	-0.061*** (0.012) [-0.084,-0.039]	-0.075*** (0.012) [-0.097,-0.052]	-0.085*** (0.012) [-0.107,-0.062]	-0.085*** (0.009) [-0.103,-0.067]
Observations	10366	10366	10366	10366	10313
Panel C: Full Controls					
Parole granted	-0.043*** (0.006) [-0.055,-0.030]	-0.053*** (0.012) [-0.077,-0.029]	-0.071*** (0.011) [-0.094,-0.049]	-0.080*** (0.011) [-0.101,-0.059]	-0.083*** (0.008) [-0.099,-0.067]
Observations	10366	10366	10366	10366	10313
Average of dep. var.	0.113	0.249	0.338	0.395	0.43

Standard errors in parentheses are clustered at the PBM level

95% confidence intervals in square brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Year Controls include year fixed effects

Year + Risk Scores Controls include year fixed effects and the eight risk scores

Full Controls adds prison fixed effects, male and Native dummies, number of dependents (categorical, top coded to 5), type of crime and age

Table 4: IV estimation

<i>Recidivism within...</i>	(1) 1 Year	(2) 2 Years	(3) 3 Years	(4) 4 Years	(5) 5 Years
Panel A: Year Controls					
Parole granted	-0.039 (0.040) [-0.117,0.040]	-0.085** (0.035) [-0.154,-0.016]	-0.074* (0.042) [-0.156,0.007]	-0.102** (0.049) [-0.199,-0.005]	-0.094* (0.054) [-0.199,0.012]
Observations	10366	10366	10366	10366	10313
Panel B: Year + Risk Scores Controls					
Parole granted	-0.033 (0.054) [-0.138,0.072]	-0.075 (0.055) [-0.182,0.032]	-0.063 (0.048) [-0.158,0.032]	-0.091*** (0.034) [-0.158,-0.023]	-0.082** (0.036) [-0.152,-0.011]
Observations	10366	10366	10366	10366	10313
Panel C: Full Controls					
Parole granted	-0.014 (0.031) [-0.075,0.046]	-0.058 (0.045) [-0.146,0.029]	-0.055 (0.048) [-0.150,0.040]	-0.084** (0.038) [-0.159,-0.010]	-0.087** (0.041) [-0.167,-0.007]
Observations	10366	10366	10366	10366	10313
Average of dep. var.	0.113	0.249	0.338	0.395	0.43

Standard errors in parentheses are clustered at the PBM level

95% confidence intervals in square brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Year Controls include year fixed effects

Year + Risk Scores Controls include year fixed effects and the eight risk scores

Full Controls adds prison fixed effects, male and Native dummies, number of dependents (categorical, top coded to 5), type of crime and age

Panel C further adds all other controls. We find that parole significantly decreases recidivism in the long run. Our estimates show statistically significant decreases of about 8 percentage points in recidivism within four and five years. The effect in the shorter run are not significant. A potential explanation is that the rehabilitative effect of parole could be counterbalanced in the short-run by the reduced incapacitation period. Interestingly, the 2SLS results are nearly identical to the OLS results that control for the risk scores, suggesting that the scores may capture most of the selection into the treatment.

We next divide our sample into different subsets to evaluate the presence of heterogeneous treatment effects. Firstly, we distinguish between low-risk and high-risk offenders. We define the low-risk group as inmates with a total LS/CMI score below 23, the median risk score in the entire sample, while the high-risk group comprises the remaining inmates—those with scores

greater or equal to 23. We find that the low-risk group drives most of the effects with treatment effects ranging from 7 to 12 percentage points. In contrast, the treatment effect for high-risk inmates are imprecisely estimated and indistinguishable from 0. Secondly, we estimate strong effects of parole on recidivism for inmates aged 36—the median age in the sample—or more whereas we find no evidence of causal effects for younger individuals. With regards to the type of crime committed, the estimates are rather noisy due to smaller sample sizes. Nevertheless, we find suggestive evidence of strong treatment effects for inmates in the *other* category—which mostly includes street gang crimes and illegal use of weapons—in the short term, while inmates convicted from burglary and theft seem to benefit from parole in the long term.

Table 5: IV estimation—Heterogeneity

<i>Subsample</i>	Recidivism within...				
	(1) 1 Year	(2) 2 Years	(3) 3 Years	(4) 4 Years	(5) 5 Years
Risk score < 23	-0.037 (0.026)	-0.076*** (0.020)	-0.081*** (0.030)	-0.097*** (0.030)	-0.121** (0.048)
Observations	4996	4996	4996	4996	4968
Risk score ≥ 23	-0.024 (0.083)	-0.059 (0.090)	-0.032 (0.082)	-0.072 (0.053)	-0.036 (0.050)
Observations	5370	5370	5370	5370	5345
Age < 36	-0.004 (0.058)	-0.023 (0.075)	0.023 (0.094)	-0.081 (0.077)	-0.084 (0.073)
Observations	4964	4964	4964	4964	4934
Age ≥ 36	-0.062 (0.058)	-0.134** (0.053)	-0.160*** (0.041)	-0.119*** (0.033)	-0.101*** (0.032)
Observations	5402	5402	5402	5402	5379
Crime = Other	-0.113* (0.061)	-0.205*** (0.053)	-0.131 (0.093)	-0.157* (0.092)	-0.112 (0.105)
Observations	2104	2104	2104	2104	2096
Crime = Assault	-0.040 (0.051)	-0.051 (0.054)	-0.135** (0.060)	-0.090 (0.057)	0.013 (0.080)
Observations	1556	1556	1556	1556	1550
Crime = Burglary and Theft	0.044 (0.112)	0.023 (0.108)	-0.034 (0.068)	-0.104* (0.057)	-0.121** (0.048)
Observations	2657	2657	2657	2657	2647
Crime = Drugs	-0.030 (0.029)	-0.062 (0.054)	0.014 (0.058)	-0.013 (0.040)	-0.051 (0.044)
Observations	4049	4049	4049	4049	4020

Standard errors in parentheses are clustered at the PBM level

95% confidence intervals in square brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Controls include year fixed effects and the eight risk scores.

4.3 Incarceration Time: Decomposing the Effect

The total time spent incarcerated is a critical outcome when studying the effects of parole. We may decompose the total effect of parole on incarceration time into the three effects illustrated in Figure 4, in which the hatched bars represent incarceration periods. The effects shown in the figure are calibrated with our results, in days, presented below. First, the main effect of parole is to decrease the incarceration time by releasing offenders sooner. In our context, parolees are released at the third of their sentence whereas non-parolees are released at the two-thirds of their sentence. Inmates who are granted parole see their incarceration time mechanically imputed by one-third. We call this effect the *release effect*. This release effect may prove a significant benefit of parole if this additional release time does not generate new crimes.

Second, the direct release effect will in some cases be partly counterbalanced by *technical violations* of parole conditions. Parole agents have latitude over the violations they report. If a technical violation is reported, parole is revoked and the inmate is reincarcerated.⁸

Third, because it usually comes with rehabilitation support, parole could affect the subsequent behavior of parolees. The previous sections showed that parole decreases the likelihood of recidivism, suggesting that it may decrease incarceration time in future sentences. We call this effect the *future sentences* effect. It captures the difference in incarceration time due to new offenses only (i.e., excluding the current sentence and the current sentence’s technical violations). Finally, the sum of the *release*, *technical* and *future sentences* effects is the *total* effect, that is, the overall change in incarceration time due to parole.

To separate these components, we estimate the causal effect of parole for each of components of incarceration time using our instrumental variable strategy, presented in the previous section, modifying only the dependent variable. Focusing on a time window of five years after the parole hearing (and excluding from the sample inmates who cannot be observed for at least 5 years), we estimate the model for each of the following dependent variable:

- *Direct release time*. It is equal to the total remaining incarceration time during the current period starting at the third of the sentence. This variable equals 0 for a parolee, and $\frac{1}{3S}$ for a non-parolee, where S is the total sentence duration. It excludes technical violations.
- *Technical violations reincarceration time*. It is equal to the total incarceration time solely due to parole violations. This variable equals 0 for non-parolees.
- *Future sentences incarceration time*. This variable sums up the inmate’s total future in-

⁸The inmate will be reincarcerated for the two-thirds of the remaining sentence length.

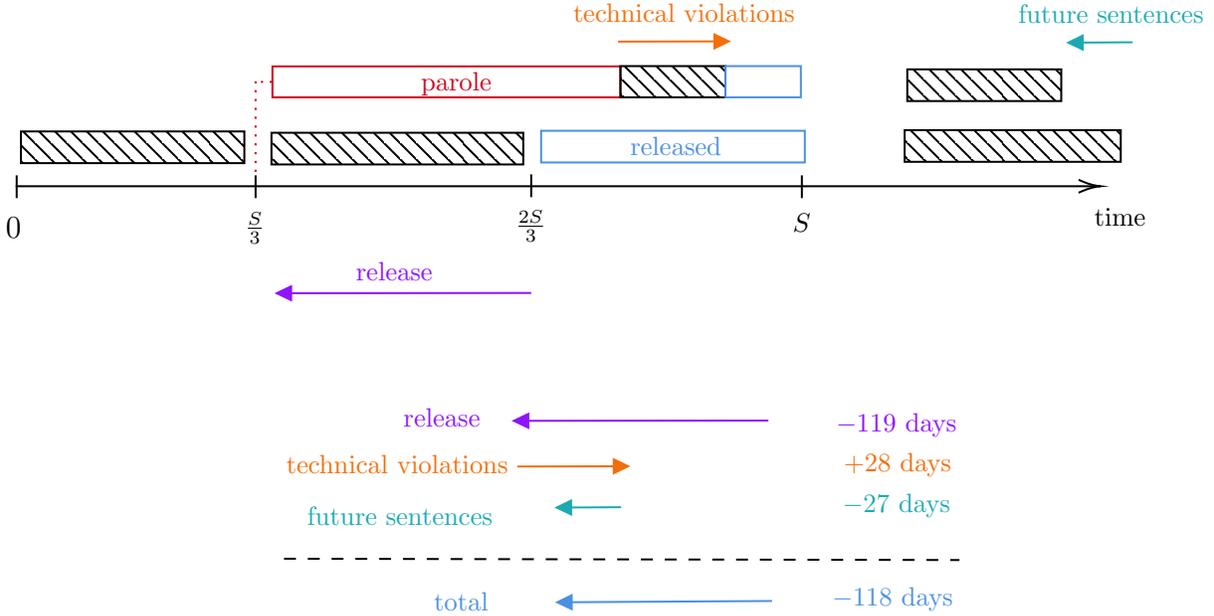


Figure 4: Decomposition of the Effect on Prison Time

Notes: This figure illustrates the potential effects of parole on incarceration time. Hatched bars represent incarceration periods. At the one-third of the initial sentence length S , the offender may either be released under parole and be subject to parole conditions until S , or remain incarcerated until $2S/3$, after which no condition applies. “Release” depicts the effect of releasing an offender sooner under parole. “Technical violation” depicts the effect of rearrests due to technical violations of parole conditions. “Future sentences” depicts the effects of future sentences caused by recidivism. “Total” is the sum of these three effects. Each effect is calibrated from the estimates from our preferred specification presented below.

carceration time due to new offenses (i.e., excluding rearrests due to the current sentence’s technical violations) within 5 years.

- *Total incarceration time.* This variable sums up the inmate’s total incarceration time starting at the parole hearing.

Table 6 presents the results. Column (1) shows that, ignoring technical violations, parolees on the margin of remaining incarcerated spend on average around 119 fewer days in prison in their current sentence because they are on parole. Column (2) reveals that this effect is, on average, counterbalanced by a return in prison of about 28 days in the current sentence because of technical violations. Column (3) suggests that parole has a rehabilitative effect and decrease incarceration time by around 26 days for future sentences, consistent with our results from previous sections. Overall, the total effect of parole is a reduction of around 117 days. These results support our conclusion that parole, in our context, successfully decreases total incarceration time while reducing recidivism.

Table 6: IV Estimation—Incarceration Time

	(1) Release	(2) Technical Violations	(3) Future Sentences	(4) Total
Panel A: Year Controls				
Parole granted	-118.868*** (5.766) [-130.170,-107.566]	27.424*** (4.374) [18.851,35.997]	-25.967*** (4.928) [-35.625,-16.309]	-117.411*** (6.388) [-129.931,-104.890]
Observations	10110	10110	10110	10110
Panel B: Year + Risk Scores Controls				
Parole granted	-118.620*** (5.697) [-129.785,-107.454]	28.232*** (2.643) [23.051,33.413]	-26.575*** (3.969) [-34.355,-18.796]	-116.963*** (6.809) [-130.308,-103.618]
Observations	10110	10110	10110	10110
Panel C: Full Controls				
Parole granted	-118.967*** (7.211) [-133.101,-104.834]	28.270*** (3.465) [21.478,35.062]	-25.949*** (4.741) [-35.241,-16.656]	-116.646*** (8.074) [-132.470,-100.822]
Observations	10110	10110	10110	10110

Standard errors in parentheses are clustered at the PBM level

95% confidence intervals in square brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Year Controls include year fixed effects

Year+ Risk Scores Controls include year fixed effects and the eight risk scores

Full Controls adds prison fixed effects, male and Native dummies, number of dependents (categorical, top coded to 5), type of crime and age

4.4 The Role of Halfway Houses

The effect of parole on recidivism could depend on the specified conditions. Such requirements—also determined by the PBM responsible for granting parole—frequently correspond to the criminogenic needs detected by the risk scores. One of these conditions appear of particular salience: whether the parolee is required to stay in an halfway house. Indeed, in our sample, 75% of parolees stay in a halfway house, and those who do have on average higher risk scores than other parolees.

As discussed previously, who gets placed into a halfway house is not random as it depends on the rehabilitation plan prepared by the inmate and other observable or unobservable characteristics. To understand better what makes parole beneficial, we modify our instrumental variable strategy to estimate the effects of parole in a halfway house for two types of compliers, using the approach proposed by [Mountjoy \(2021\)](#). He studies the effects of 2-year colleges for

compliers on two distinct margins: individuals who would not have gone to college otherwise and individuals who would have studied in a 4-year college otherwise. This approach translates well into our context. We consider three possible states:

D_0 = incarceration (parole is denied)

D_1 = parole is granted in a halfway house

D_2 = parole is granted without a halfway house requirement

Within this framework, when estimating the effect of being in a halfway house, we may conceive two type of compliers: those who would otherwise remain incarcerated ($D_0 \rightarrow D_1$) and those who would otherwise be granted parole without the requirement to stay in a halfway house ($D_2 \rightarrow D_1$). To estimate these effects, one needs an instrument for D_1 and an instrument for D_2 . We denote these instruments by z^{D_1} and z^{D_2} respectively.

We construct z^{D_1} in two steps. First, inmates, when preparing their rehabilitation plan, face a resources availability constraint because halfway houses only have a limited number of beds. Halfway houses managers often have to decline inmates' applications because of capacity constraints. This is especially true in regions with fewer halfway houses. Although our data do not allow to match parolees with the exact halfway houses they applied to, lengthy discussions with halfway houses managers revealed that most parolees prefer to contact the halfway houses nearest to the location they were living at before being incarcerated, which we proxy by the region where they are incarcerated.⁹

We define the set of parolees in halfway houses in region r during month m as \mathcal{H}_{rm} . Similarly, let \mathcal{P}_{rm} be the set of parolees regardless of whether they are staying in a halfway house. We define the resources availability measure of individual i as

$$RA_i = \frac{|\mathcal{H}_{(rm,-i)}|}{|\mathcal{P}_{(rm,-i)}|}.$$

RA_i can be interpreted as the proportion of parolees who are sent to a halfway house at the time of inmate i 's hearing, in the region they are from. To avoid any small sample bias, we create an individual measure of this share by removing individual i when computing this fraction.

Second, regardless of whether a stay in a halfway house is mentioned in the inmate's rehabilitation plan, the PBM can impose the condition. Therefore, we calculate the residualized share of inmates who are granted parole while being required to stay in a halfway house by the

⁹Inmates are usually incarcerated near their home region.

assigned PBM. We first estimate the following regression:

$$(\text{parole} \times \text{halfway house})_{ij} = \delta_0 + \delta_1 \text{year}_i + \delta_2 \text{prison}_i + \delta_3 \text{Native}_i + \eta_{ij}$$

and sum $\hat{\eta}$ at the PBM (indexed by j) level: $\tilde{\eta}_j = \sum_{i|i \in \mathcal{N}_j} \hat{\eta}_{ij}$. Then, for an inmate i who met with PBM j , the instrument is given by

$$z_{ij}^{D_1} = RA_i \times \frac{\tilde{\eta}_j - \hat{\eta}_{ij}}{|\mathcal{N}_j| - 1}.$$

Intuitively, $z_{ij}^{D_1}$ measures how likely an inmate’s application will be accepted by a halfway house and this inmate’s likelihood of being granted parole with a halfway house by the assigned PBM j .

We construct the instrument for D_2 similarly to our main instrument: $z_{ij}^{D_2}$ is the residualized share of inmates who are granted parole while *not* being required to stay in a halfway house by the assigned PBM. Specifically, we estimate the following regression:

$$(\text{parole} \times \text{no halfway house})_{ij} = \alpha_0 + \alpha_1 \text{year}_i + \alpha_2 \text{prison}_i + \alpha_3 \text{native}_i + \zeta_{ij},$$

and, using the same notation as before, we define

$$z_{ij}^{D_2} = \frac{\tilde{\zeta}_j - \hat{\zeta}_{ij}}{|\mathcal{N}_j| - 1}.$$

Table A.4 shows that both instruments are strongly correlated with the treatments, with F-statistics large enough regardless of whether characteristics are controlled for. As mentioned, the three states— D_0 , D_1 and D_2 —are not random. The first three columns of Table A.5 regress each three indicators on the full set of observable characteristics. In particular, most risk scores correlate with each decision. Yet, the instruments $z_{ij}^{D_1}$ and $z_{ij}^{D_2}$ appear to be random, as shown in columns (4) and (5). Finally, Figure B.2 shows the distribution of $z_{ij}^{D_1}$. Figure B.3 shows the distribution of the non-leave-out version of z^{D_2} , keeping one observation by PBM.

[Mountjoy \(2021\)](#) shows that the margin-specific treatment effects can be estimated for the two types of compliers. To estimate the effect of an early release in a halfway house compared to remaining incarcerated, we have that

$$\text{MTE}_{D_0 \rightarrow D_1} = \frac{\frac{\partial E(Y \times D_1 | z^{D_1}, z^{D_2})}{\partial z^{D_1}}}{-\frac{\partial E(D_0 | z^{D_1}, z^{D_2})}{\partial z^{D_1}}} - \frac{\frac{\partial E(Y \times D_1 | z^{D_1}, z^{D_2})}{\partial z^{D_2}}}{\frac{\partial E(D_1 | z^{D_1}, z^{D_2})}{\partial z^{D_2}}} \frac{\frac{\partial E(D_2 | z^{D_1}, z^{D_2})}{\partial z^{D_1}}}{\frac{\partial E(D_0 | z^{D_1}, z^{D_2})}{\partial z^{D_1}}} - \frac{\frac{\partial E(Y \times D_0 | z^{D_1}, z^{D_2})}{\partial z^{D_1}}}{\frac{\partial E(D_0 | z^{D_1}, z^{D_2})}{\partial z^{D_1}}}.$$

To get the effect of the halfway house compared to being release *without* the halfway house requirement, one can estimate:

$$\text{MTE}_{D_2 \rightarrow D_1} = \frac{\frac{\partial E(Y \times D_1 | z^{D_1}, z^{D_2})}{\partial z^{D_2}}}{\frac{\partial E(D_1 | z^{D_1}, z^{D_2})}{\partial z^{D_2}}} - \frac{\frac{\partial E(Y \times D_2 | z^{D_1}, z^{D_2})}{\partial z^{D_1}}}{\frac{\partial E(D_2 | z^{D_1}, z^{D_2})}{\partial z^{D_1}}}.$$

Each term of $\text{MTE}_{D_0 \rightarrow D_1}$ and $\text{MTE}_{D_2 \rightarrow D_1}$ can be estimated with an appropriate 2SLS regression. Because the parameters of interest are composites of several 2SLS coefficients, we estimate the standard errors by bootstrapping the process 1,000 times.

Table 7 presents the results. The first panel estimates the effect of being granted an early release in a halfway house for compliers who would otherwise remain incarcerated. We find strong and statistically significant effect of the treatment on recidivism in the short term, with reductions in the probability to recidivate of around 10 percentage points. This suggests that being granted an early release in a halfway house yields positive outcomes for those at the margin of remaining incarcerated. The bottom panel shows the effect for the other type of compliers, those who would otherwise be released on their own. Unfortunately, we do not find any conclusive evidence as the confidence intervals are too large. One reason for the imprecision of the estimates could be the lack of compliers from this specific margin.

Table 7: Effect of Halfway House on Two Types of Compliers

<i>Recidivism within...</i>	(1) 1 Year	(2) 2 Years	(3) 3 Years	(4) 4 Years	(5) 5 Years
<i>Compliers at the margin of incarceration</i>					
Half. house	-0.112**	-0.161**	-0.11*	-0.102*	-0.080
<i>(bootstrapped se)</i>	(0.056)	(0.070)	(0.076)	(0.080)	(0.081)
<i>[95 % CI]</i>	[-0.200,-0.018]	[-0.279,-0.043]	[-0.240,0.008]	[-0.230,0.031]	[-0.206,0.060]
<i>Compliers at the margin of release</i>					
Half. house	0.449	0.636	0.272	-0.275	0.111
<i>(bootstrapped se)</i>	(0.386)	(0.571)	(0.613)	(0.883)	(0.820)
<i>[95 % CI]</i>	[-0.160, 1.097]	[-0.262, 1.590]	[-0.751, 1.294]	[-1.818, 1.140]	[-1.251, 1.415]
Observations	10366	10366	10366	10366	10313
Average of dep. var.	0.113	0.249	0.338	0.395	0.43

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All estimations control for year fixed effects and for the eight components of the LS/CMI risk assessment

5 Conclusion

Our research design allowed us to estimate the causal effect of parole in a context where parolees have a relatively low risk of recidivism and where substantial rehabilitative assistance is provided to parolees. The results suggest that for individuals at the margin of remaining incarcerated in our context:

1. Parole decreases recidivism by more than 8 percentage points within five years. This effect is especially driven by lower-risk individuals.
2. Parole does not affect recidivism in the short run, potentially because the rehabilitative effect is counterbalanced by a shortened incapacitation period.
3. Parole successfully reduces incarceration time while decreasing recidivism.
4. Halfway houses that provide transitory assistance are a likely mechanism. Indeed, 75% of the parolees in our sample are required to stay in a halfway house. We find that compliers at the margin of incarceration benefit from an early release in a halfway house.

The literature would benefit from further research studying the mechanisms underlying such results. First, the selective nature of the screening process could result in halfway houses being a more positive environment with fewer disruptive peers. Second, halfway houses could provide the opportunity to get a new start at life by learning real-world skills such as running errands,

taking the bus and finding work. Third, the heightened supervision could allow the counselors to witness when parolees' lives get disorganized and to tailor interventions appropriately. One emphasized element during our discussions with halfway houses managers is the special bond between inmates and counselors. In some halfway houses, it is the counselors themselves who, with their own car, pick up parolees at the prison. In others, during the holiday season, counselors choose personalized gifts for inmates and prepare a special dinner for them. Whether or not creating such a friendly environment is an important ingredient of a successful rehabilitation is an important question.

Our design does not allow separating two mechanisms: whether the effect stems from the early release itself (being released sooner) or from the assistance being provided during this release. More research is needed to determine the specific practices and conditions that lead to lasting reintegration. Yet, our results point to supervised transition as an actionable way for fostering effective reentries into community.

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A Additional Tables

Table A.1: First Stage: Parole Decision

	(1) Parole	(2) Parole
z^p	1.242*** (0.060)	1.019*** (0.054)
N	10366	10366
Controls	Year	Full
F-stat (excl. inst.)	429.09***	356.20***

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The F statistic tests the significance of the excluded instrument

Year Controls include year fixed effects

Full Controls adds prison fixed effects, male and Native dummies, number of dependents (categorical, top coded to 5), type of crime and age

Table A.2: First Stage: Various Subsamples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Age < median	Age ≥ median	Assault	Burglary and Theft	Drugs	Other crimes	Male	Female	Native	Non-native
z^p	1.275*** (0.086)	1.203*** (0.084)	1.556*** (0.148)	1.447*** (0.115)	0.997*** (0.095)	1.220*** (0.133)	1.269*** (0.062)	0.918*** (0.227)	2.024*** (0.252)	1.200*** (0.062)
Observations	4964	5402	1556	2657	4049	2104	9633	733	382	9984

Robust standard errors in parentheses
 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: First Stage: Across the Distribution

<i>Interval</i>	$-.11 \leq z^p \leq -.04$	$-.04 \leq z^p \leq 0$	$0 \leq z^p \leq .12$
z^p	2.816*** (0.328)	5.813*** (0.579)	1.249*** (0.234)
Observations	3446	3464	3456

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All regressions include year fixed effects

The instrument z^p was cut into three equally-sized groups

Table A.4: Mountjoy: First Stage

	(1)	(2)	(3)	(4)
	Halfway House	Halfway House	No Halfway House	No Halfway House
z^{D_1}	1.970*** (0.127)	1.364*** (0.124)		
z^{D_2}			0.842*** (0.083)	0.782*** (0.076)
N	10366	10366	10366	10366
Controls	Year	Full	Year	Full
F-stat (excl. inst.)	239.45***	120.36***	101.97***	107.23***

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Year Controls include year fixed effects

Full Controls add all remaining variables

The F statistic tests the significance of the instrument

Table A.5: Mountjoy: Randomization Tests

	(1)	(2)	(3)	(4)	(5)
	Incarceration	Halfway House	No Halfway House	z^{D_1}	z^{D_2}
RS-Criminal History	0.041*** (0.003)	-0.008*** (0.003)	-0.033*** (0.002)	0.000 (0.000)	-0.000 (0.000)
RS-Education/Employment	0.007*** (0.002)	0.007*** (0.002)	-0.014*** (0.001)	-0.000 (0.000)	-0.000 (0.000)
RS-Family/Marital	0.008* (0.004)	0.007 (0.004)	-0.015*** (0.003)	0.000 (0.000)	-0.000 (0.000)
RS-Procriminal Attitude	0.103*** (0.004)	-0.087*** (0.004)	-0.016*** (0.003)	-0.001** (0.000)	-0.000 (0.000)
RS-Companions	0.002 (0.005)	0.010* (0.006)	-0.012*** (0.003)	0.000 (0.000)	-0.000 (0.000)
RS-Leisure/Recreation	0.015** (0.008)	0.015* (0.008)	-0.030*** (0.005)	0.001 (0.001)	0.001 (0.001)
RS-Alcohol/Drugs	0.009*** (0.002)	0.002 (0.002)	-0.011*** (0.001)	0.000 (0.000)	-0.000 (0.000)
RS-Antisocial Pattern	0.004 (0.006)	-0.014** (0.006)	0.009*** (0.003)	-0.001 (0.001)	0.000 (0.001)
Age	0.003*** (0.000)	-0.003*** (0.000)	0.000 (0.000)	-0.000* (0.000)	0.000 (0.000)
Crime: Assault	0.054*** (0.015)	-0.028* (0.015)	-0.027*** (0.009)	-0.000 (0.001)	-0.001 (0.001)
Crime: Burglary and theft	-0.002 (0.013)	0.022* (0.013)	-0.020*** (0.008)	-0.001 (0.001)	-0.003** (0.001)
Crime: Drugs	-0.066*** (0.012)	0.053*** (0.012)	0.013 (0.009)	-0.000 (0.001)	-0.002 (0.001)
Number of dependants=1	0.020 (0.015)	-0.027* (0.015)	0.007 (0.010)	-0.001 (0.001)	-0.002 (0.001)
Number of dependants=2	0.018 (0.017)	-0.027 (0.018)	0.009 (0.013)	0.001 (0.001)	0.000 (0.002)
Number of dependants=3	-0.008 (0.025)	-0.018 (0.027)	0.026 (0.020)	-0.001 (0.002)	0.002 (0.003)
Number of dependants=4	-0.020 (0.039)	-0.016 (0.039)	0.037 (0.032)	-0.003 (0.003)	-0.002 (0.004)
Number of dependants=5	0.133*** (0.044)	-0.076* (0.042)	-0.057*** (0.021)	-0.005 (0.004)	-0.005 (0.004)
Constant	-0.022 (0.023)	0.508*** (0.025)	0.514*** (0.020)	0.002 (0.002)	0.002 (0.002)
N	10366	10366	10366	10366	10366
Controls	Year	Year	Year	Year	Year
F-stat	216.25***	55.11***	85.25***	1.50*	1.00

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Year Controls include year fixed effects

The F statistic tests the significance of the short regression

B Additional Figures

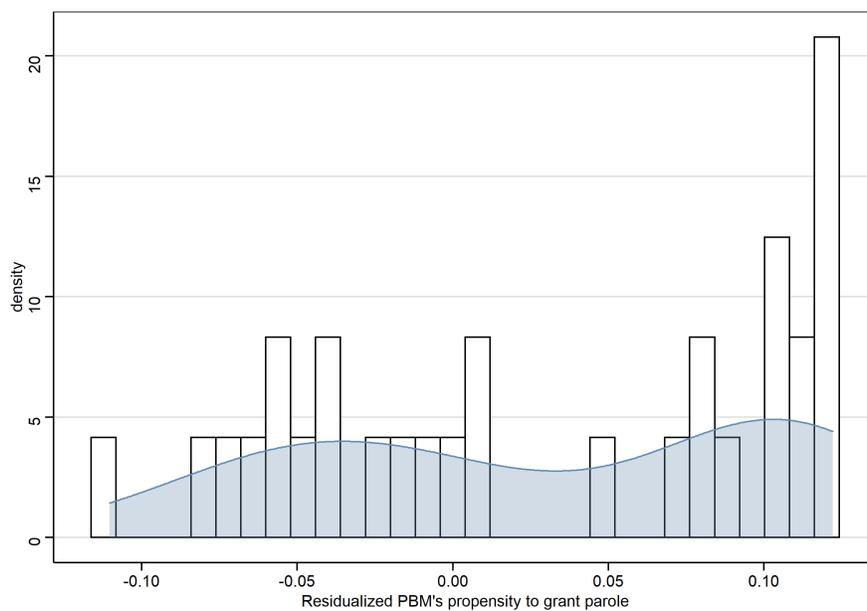


Figure B.1: Density of z^p

Note: This figure presents the density of the non-leave-out version of the residualized parole board member (PBM) propensity to grant parole, which is used as an instrument used in our main IV estimation. We keep one observation by PBM.

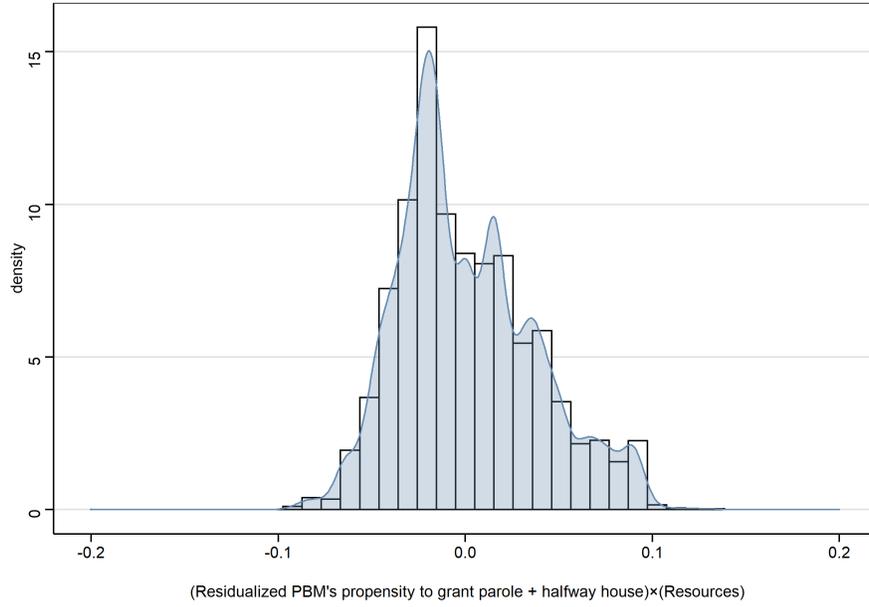


Figure B.2: Density of z^{D_1}

Note: This figure presents the density of our constructed z^{D_1} variable, which is used as an instrument in our IV estimation for two groups of compliers.

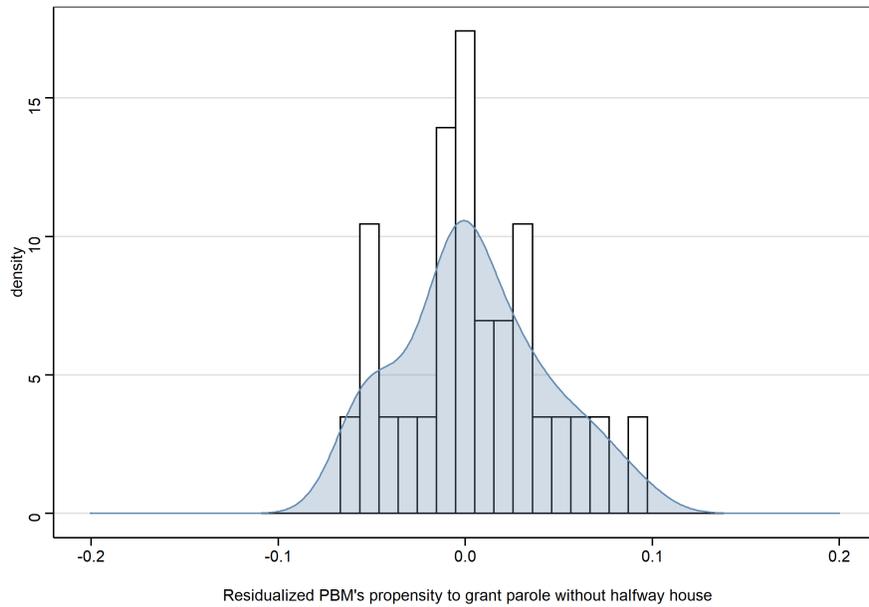


Figure B.3: Density of z^{D_2}

Note: This figure presents density of the non-leave-out version of z^{D_2} , which is used as an instrument in our IV estimation for two groups of compliers. We keep one observation by PBM.

Parole, Recidivism, and the Role of Supervised Transition

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