First-Day Criminal Recidivism

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Abstract: We report that on any given day the number of inmates released from incarceration significantly affects the number of offenses committed this day, and we name this as first-day recidivism. Our estimates of this novel approach to study early recidivism are robust to a variety of alternative model specifications. We then show that first-day recidivism can be eliminated by an increase in the gratuity provided to prisoners at the time of their release. A simple cost-benefit analysis shows that increasing the gratuity at release is a very efficient policy.

Keywords: Recidivism; property crime; liquidity constraints.

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I. Introduction

Criminal recidivism of former prisoners is a widespread phenomenon. Recidivism rates are 65 percent in the United States (Langan and Levin 2002), 60 percent in the Netherlands (Nieuwbeerta, Nagin, and Blokland 2009), 58 percent in England and Wales (Cuppleditch and Evans 2005), and 60 percent in Uruguay (IACHR 2011), to mention a few examples. In addition, evidence indicates most criminal recidivism occurs within the first year after release (Langan and Levon 2002). For example, in the United States criminal recidivism within the first year after release is around 44 percent. Similar figures apply in Australia (Jones et al. 2006).

In this paper we provide a novel approach to study criminal recidivism. In particular, we focus on recidivism during the first day of freedom, what we name "first-day recidivism." Using a unique database on crime and releases from Montevideo, Uruguay, we find the number of inmates released on a given day significantly affects the number of offenses committed this day, and we interpret this result as evidence of first-day recidivism. The dynamics of the relationship between crime and releases shows that inmate releases increase crime on the very day of the release but have no effect on crime in subsequent days. This finding points to some special first-day effect and suggests that release policies focusing on preventing first-day recidivism might be effective in reducing crime. Here we focus on the stipend that prisoners receive upon release. We find that an increase in the gratuity at release produces a sharp decrease in first-day recidivism, a decrease that is not compensated by an increase in crime in the following days. The fact that increasing the stipend given to prisoners upon release affects the propensity of released prisoners to engage in criminal behavior is both novel and important from a policy perspective.

Our findings on first-day criminal recidivism are robust to the inclusion of day of the week and year/month fixed effects, and also to controlling for holidays, rainfall, sunshine, and temperature. We also applied a Lasso-type procedure for variable selection proposed by Belloni, Chernozhukov, and Hansen (2014) that starts to iterate with a highly saturated model and the coefficient of interest remains significant. Given the time-series nature of the exercise at hand, inference is always a concern. To deal with potential deviations of standard homogeneity assumptions, we apply the asymptotic approach proposed by Canay, Romano, and Shaikh (2013) and all results remain unchanged.

We further explore the reasons underlying first-day recidivism. We report that first-day recidivism is observed for crimes that have a financial motivation (property crimes such as thefts and robberies) and not for other types of offenses (non-property crimes such as assaults and domestic violence), findings consistent with a rational framework in which offenders have liquidity constraints, as in Jacob, Lefgren, and Moretti (2007).

Our paper contributes to the literature on criminal recidivism. The criminology literature defines criminal recidivism as a time interval between two events (Maltz 1984): a release event (usually from incarceration) and a failure event (re-arrest or reconviction).[1] Here, we focus on the estimation of re-offenses instead of following the usual procedure of using records on re-arrest or re-conviction, allowing in this way the inclusion of a large pool of offenses usually omitted in standard statistics.[2] To the best of our knowledge, our paper provides the first estimates on the magnitude of the re-offence rate during the very day prisoners are released.

Our findings are related to the literature on the effects of incarceration rates on crime. While estimated magnitudes are sensitive to the estimation methodology, most careful research finds that an increase in incarceration rates leads to a reduction in crime. Incarceration, however,

[1] The release event could also be from electronic monitoring or any other type of official custody.

[2] Harrendorf, Heiskanen, and Malby (2010) consider more than 100 countries in the United Nations' International Statistics on Crime and Justice and report high levels of attrition between the commitment of a crime and the arrest or conviction of the offender (50 percent of offenders are arrested and 19 percent are convicted). In Uruguay only 25 percent of the police-recorded offenses are prosecuted.

has two effects on criminal behavior: deterrence and incapacitation. A deterred offender is able to commit crime but chooses not to, whereas an incapacitated offender would choose to commit crime but is unable to. There is an important body of literature that tries to isolate pure incapacitation effects. Marvell and Moody (1994) use inmate interviews on criminal activity prior to arrest to calculate the offenses that inmates would have committed had they not been incarcerated and report a crime-prison elasticity of -0.16. Levitt (1996) uses prison-overcrowding litigation in the United States as an instrument for state level incarceration rates and reports crime-prison elasticities between -0.26 and -0.42. Johnson and Raphael use data for the period 1978 to 1990 in the United States and conclude that each additional prison year served prevents 14 reported serious crimes. Owens (2009) uses quasi-experimental variation in sentence length created by a change in Maryland law that reduced the recommended sentences for a group of individuals between 23 and 25 years old with delinquent records by a mean of 222 days per delinquent "point." She finds that offenders were on average arrested for 2.8 criminal acts and were involved in between 1.4 and 1.6 index crimes per person during the period in which they would have otherwise been incarcerated. More related to our approach, two recent papers exploit the natural experiment generated by massive releases in Italy (which liberate approximately one third of the prison population) to estimate the reverse incapacitation effect. Barbarino and Mastrobuoni (2014) estimate an elasticity of crime with respect to incarceration of around -0.20. Buonanno and Raphael (2013) report that each prison year served prevents 14 to 18 crimes. Our contribution to this literature is to use high-frequency data that allows us to estimate a very short-run reverse incapacitation effect.

Our estimates indicate that first-day recidivism accounts for a 0.8 percent increase in Montevideo's property crimes, a relatively small effect from a criminal justice point of view.

However, our estimates also suggest that approximately one out of four prisoners commit a crime on the very day of release, a very large effect from an individual perspective.

Our work also contributes to a recent discussion on release policies. Release policies have received little attention in the economics literature, an omission that is unfortunate considering that, only in the Unites States, approximately six hundred thousand prisoners are released every year (BJS 2002), and an important share of crime is committed by the newly released (see, for example, Raphael and Stoll 2004). Release policy has several relevant dimensions. In a recent work, Kuziemko (2013) compares discretionary parole and fixed-sentence regimes and reports evidence that parole boards appear to perform better in terms of reducing recidivism compared to regimes in which inmates' original sentences are binding. Di Tella and Schargrodsky (2013) study the re-arrest rates of individuals released from prison and individuals released from electronic monitoring, and report that there is a large, negative causal effect (up to 40 percent) on criminal recidivism of treating individuals with electronic monitoring relative to prison. In a related paper, Marie (2013) studies the electronic monitoring release policy in England and Wales, and finds that early electronic monitoring release reduces the chances of re-arrest of ex-prisoners by between 20 and 40 percent within two years. In this paper we study another dimension of release policy: the effect of the gratuity given at release on very early recidivism rates.[3] There is a related literature in the early 1980s, mainly in sociology. Rossi, Berk, and Lenihan (1980) and Mallar and Thornton (1978) analyze a randomized experiment in which unemployment benefits were extended to individuals immediately upon release from prison. They find significantly fewer re-arrest for property crimes within the year. Berk, Lenihan, and Rossi (1980) analyze two related experiments

[3] There is no pattern around the world on what prisoners receive when released from prison. In Ireland, Sweden, and Argentina released prisoners receive the money earned by working while in prison; in Mexico and Estonia the prisoners are forced to save a portion of this income until the moment of liberation. In Australia, Canada, the Netherlands, and South Africa the prison authorities must ensure that former prisoners have enough funds to return to their homes, even by providing funds if necessary. There are also some examples such as Chile where the government does not provide any allowance to released interns.

and report that modest transfer payments (again in the form of unemployment benefits) reduce recidivism in the twelve-month period following release from prison. There is also a related literature on job market opportunities and recidivism. Schnepel (2013) find that an increase in the prevalence of relevant employment opportunities is associated with an important decrease in the probability that released offenders will return to prison within one year.

Our results on the effects of an increase in the payment received by prisoners at release are in line with the empirical evidence on the effects of cash transfers on crime. Loureiro (2012) and Chioda, De Mello, and Soares (2012) find a negative relationship between conditional cash transfers and property crime in Brazil. Similar results are found in Colombia (Camacho, Mejía, and Ulloa 2013). Jacob and Ludwig (2010) analyze a housing voucher program (that increases cash income from reductions in out-of-pocket spending on housing) in Chicago and report a decrease in arrests. DeFronzo (1996, 1997), Zhang (1997), Hannon and DeFronzo (1998), and Foley (2011) study the impact of the amount and timing of welfare payments in United States. Interestingly, they find the liquidity provided by the monthly payments not only reduces crime, but also affects the timing of offenses during the month.

The paper continues as follows. Section II describes the data. Section III reports the results. Section IV concludes.

II. Data

Our dataset includes the universe of criminal incidents reported at the Police Department of Montevideo: more than 690,000 felonies reported in Montevideo, the capital of Uruguay, between January 1st 2004 and March 15th 2011 (2,631 days).[4] The two most frequent types of crime are theft and robbery. Theft is defined as depriving a person of property without the use of violence (61 percent of all police-recorded offenses in Montevideo in our sample period), whereas robbery

[4] Montevideo has a population of 1.5 million of inhabitants, roughly half of the population of the country.

is defined as depriving a person of property with the use or threat of violence (9 percent of the offenses in our database). There is an average of 270 offenses per day of which 192 correspond to property crime (165 thefts and 27 robberies) and 78 to non-property crime. Daily and monthly patterns of crime are shown in Figure 1.

Aside from crime data, our database includes daily information on average temperature (degrees centigrade), rainfall (millimeters), and hours of sunshine. The literature has long recognized that weather is strongly correlated to crime, with hotter weather generally associated with more crime and rainfall with less crime (Cohn 1990; Field 1992; Jacob, Lefgren, and Moretti 2007). Summary statistics are reported in Table 1.

Our dataset also includes daily information on the number of inmates released from *ComCar* (Complejo Carcelario Santiago Vázquez), the main detention center of Montevideo. Covering close to 80 percent of the city's penal population, *ComCar* penitentiary center is also the largest correctional facility in Uruguay (hosting approximately 3,200 of the 9,200 inmates in Uruguay). More than 70 percent of the prisoners at *ComCar* come from remarkably high social vulnerability backgrounds, 92 percent of inmates did not graduate from high school, and only 38 percent held a job in the formal economy before incarceration (JND 2007). The overcrowding rate in *ComCar* averaged 170 inmates per 100 slots during the period 2004 to 2010, well above the *United Nations Standard Minimum Rules for the Treatment of Prisoners* threshold of 120 inmates per 100 slots available. Living conditions for the inmates are inadequate (IACHR 2011). In addition, rehabilitation and social reinsertion activities are practically absent as opportunity to engage in productive activities when convicted are very scarce (UN 2007).

On average six inmates are released from *ComCar* every day. In our sample period, about half of the inmates were released after a conviction for theft and ten percent after a conviction for robbery. Almost 90 percent of the inmates released are single and most of them are young (at release, 36 percent of the inmates were aged between 18 and 24, and 25 percent between 25 and 29). Figure 1 shows average number of releases by day of the week (Monday to Sunday) and by day of the month (31 days). Most prisoners are released during the week (an average of 6 releases compare to 0.6 releases during weekends and holidays), and there are no significant differences in the number of inmate released throughout the month. Figure 2 presents histograms for releases and total crime.

We claim that releases are exogenous in a model for daily crime. The bureaucratic burden needed to release a prisoner implies that the exact day of release is very difficult to predict in advance. In addition, prison authorities have no discretion in the release policy; daily releases proceed as soon as dated official notification comes from the judge, and without this signed paper prison authorities are unable to open the door.

Under the usual procedure, inmates are informed of their pending release as close as one day prior to actual release. Even though inmates have fixed sentences, mainly due to good behavior, they are usually released before the end of the original sentence. Given *ComCar* authorities do not inform the inmate's families of any details pertaining to the release, the former prisoner typically leaves the conviction center alone (the prisoners that are liberated on a given day are not released all together, but individually). When released ex-inmates cannot take anything with them, other than the clothes they wear.

III. Results

First-day criminal recidivism

We are first interested in estimating the impact of the number of inmates released on a given day on the number of offenses committed this day. Formally, we want to estimate the following equation:

$$Offenses_t = \alpha + \beta\, Releases_t + \varphi\, X_t + \varepsilon_t \quad (1)$$

where $Offenses_t$ is the total number of offenses on day t, $Releases_t$ is the total number of inmates released on day t, β is the parameter of interest, and ε_t is the error term. The set of controls, X_t, includes temperature, rainfall, hours of sunshine, holidays, and a dummy for the 31st of December (a day that systematically presents a very small number of offences).[5] Depending on the particular specification, we include day of the week dummies (Monday to Sunday), year dummies (2004 to 2011), dummies for month and year combinations, and/or a time trend (daily, monthly, or yearly).

Given that all the series are stationary according to standard unit root tests,[6] we estimate equation (1) using Ordinary Least Squares (OLS). In column (1) of Table 2 we report estimates of equation (1) including a yearly trend. The coefficient on the total number of inmates released is positive and statistically significant. The value of the coefficient implies an increase of one reported crime for every four inmates released.

In the remaining columns in Table 2 we show the results are robust to alternative specifications. Results remain unchanged when we either include a daily or a monthly trend instead of a yearly one (columns (2 and 3)), an intra-month daily trend, (column (4)), or when we saturate the model with dummies for month and year combinations (our preferred specification, column (5)).

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[5] December 31st is an outlier in every year of the sample. The average number of crimes reported in this day is only 7, a figure that compares to an average of 269 crimes in December 29th, 270 in December 30th, 261 in January 1st, and 249 in January 2nd.

[6] The Augmented Dickey-Fuller Test (MacKinnon (1996) rejects the null hypothesis that the time series Offenses and Releases have a unit root at the 1 percent level. All results mentioned but not shown are available from the authors upon request.

Results are also robust to controlling for the characteristics of the inmates released (proportion of releases by type of crime committed, age range, and marital status, see column (6)). The coefficient on *Releases* drops from 0.23 to 0.18 when we include the set of controls. Notice, however, that the sample size shrinks from 2,631 to 2,068 observations because we do not have demographic data for every day of the sample size. To check if the size of the coefficient drops due to the presence of covariates or to the different sample available, we run model (5) in the same sample of model (6). As reported in model (7), the value of the coefficient in this specification is close to 0.20, suggesting that much of the drop in the value of the coefficient is due to the difference in the sample. In addition, the coefficients of all the characteristics of the inmates released are statistically not significant suggesting that the specification without controls is more appropriate than the specification with controls.

Finally, we applied a Lasso-type procedure for variable selection (the post-double-selection method proposed by Belloni, Chernozhukov, and Hansen (2014)). As reported in column (8), the coefficient on the total number of inmates released is higher in this specification, and it remains significant at the 1 percent level. The selection algorithm starts the iteration with a broad set of controls that includes temperature, rainfall, hours of sunshine, plus interactions and all squares of those controls. It also includes dummies for day of the week (Monday to Sunday), day of the year (1 to 366), day of the month (1st to 31st), month (January to December), year (2004 to 2011), and month/year combinations (96 months) and a time trend (linear, squared, cubed, and to the fourth). This gives us a set of 530 control variables to select among in addition to the control variables for temperature, rainfall, hours of sunshine, holidays, and the characteristics of the inmates released that we include in every model.[7] Notice that the approach allows the number of potential controls

[7] The selected model includes, in addition to the controls and inmates characteristics, dummy variables for Friday and Saturday plus squared Temperature and squared Sunshine.

to be much larger than the sample size and, once the model is selected, inference on the coefficient of interest can be performed using conventional methods for parameters estimated by least squares.

In all models the coefficients of the control variables are as expected: total crime increases with temperature, and decreases with rainfall and on holidays. Hours of sunshine are positively correlated with crime. The coefficients of the day of the week dummies show similar crime levels from Monday to Thursday and on Saturdays, a crime peak on Fridays, and a decrease on Sundays, in line with the pattern displayed in Figure 1. The coefficients of the month dummies (not reported) show December and January are the months with the lowest levels of crime.

Inference can be a concern with time-series data. To deal with potential heteroskedasticity and serial correlation we follow the standard approach of reporting Newey-West robust standard errors. In addition, we apply the asymptotic approach proposed by Canay, Romano, and Shaikh (2013) and the main coefficient remains significant in all the models reported in Table 2.[8] This approach works under weak conditions on the degree of dependence (the assumption is weak convergence) and heterogeneity of the distribution of the data, which suggests that our results are robust to deviations of standard homogeneity assumptions.

As observed in Figure 1, most of the releases take place in weekdays. Thus, we expect that most of the action on first-day recidivism should come from weekdays. As shown in column (1) of Table 3, this is exactly the case: results remain unchanged when we restrict the sample to weekdays. The coefficient on *Releases* remains positive and significant when we exclude one day of the weekdays at the time, as reported in columns (2) to (6) of Table 3, except when we exclude Wednesdays from the sample. In addition, in column (7) we report a specification where *Releases* is interacted with day of the week (Monday to Sunday). In this specification we cannot reject the

[8] We divided the data in 10 clusters. Results are also robust to changes in the number of clusters (12, 14, 16, 18, and 20 clusters). The R-code is available from the authors upon request.

hypothesis that all the interaction terms corresponding to Monday to Friday are equal, thus indicating that first-day recidivism are statistically similar on every day from Monday to Friday. The results also indicate that there is no effect on weekends.

In Table 4 we explore the dynamics of first-day recidivism. We analyze various structures of lags (from t-1 to t-7) and in all cases the number of releases is not related to crime in the following days, indicating that the correlation between crime and the number of inmates released is significant only in the same day of the release.[9] We also include total crime as a lagged dependent variable. The coefficient associated to Total Crime in t-1 is significant but relatively small. In column (5) we include accumulated releases from the previous seven days and the coefficient on the same day releases remain unchanged.

In order to ensure the results indeed do have a causal interpretation, we run a series of placebo exercises. In the first exercise, we correlate the number of offenses in a given day with the number of releases on the following day (column (1) in Table 5). The specification also includes the releases of the day and from the previous day. As expected, we find no significant association between crime and future releases; the only significant coefficient in this specification is the one associated to releases in the same day.

In the second exercise, we exploit intra-day variation in the data. For the period January 1st 2004 to December 30th 2010 we were able to construct four additional series: total crime before 6am, total crime between 6am and noon, total crime between noon and 6pm, and total crime after 6pm. Given that inmates are never released before the dawn, we should not observe any correlation between releases and offenses before 6am. As shown in column (2) of Table 5, this is exactly what we find. Indeed, as reported in columns (3) to (5), all the effect is concentrated between 6am and 6pm.

[9] The conclusions remain unchanged when we include one lag at the time.

In the third exercise, we exploit the fact that we know the jurisdiction where the crime is committed. Given that much of the effect is driven by crime that occurs immediately upon release, we might expect crimes to occur mostly near the prison itself. To generate a proxy of the distance to the prison we divide Montevideo into two separate areas: the within-range area and the out-of-range area. The within-range area is made up of every jurisdiction (Montevideo has 24) a prisoner can easily access after release; the out-of-range area contains the remaining jurisdictions. Regions are determined by including all destinations a prisoner may reach on foot or by bus, within an estimated one and a half hour timeframe from leaving the prison (see Figure 3).[10] The within-range area encompasses 71 percent of the population, 66 percent of the area, and hosts 74 percent of the crime in Montevideo. As shown in columns (6) and (7), the number of released inmates significantly affects total offenses in the within-range area, and there is no significant effect of releases on total offenses in the out-of-range area. Results are robust to alternative definitions of the within-range areas.

Overall, these exercises further corroborate the empirical validity and the robustness of our results.

The impact of increasing the gratuity at release

Having established evidence on first-day criminal recidivism, we now ask whether it is possible to prevent it. To do so, we explore the impact of an exogenous increase in the gratuity at release on first-day recidivism. On September 6th 2010 the gratuity at release was multiplied by 3⅓ (from UR$ 30 to UR$ 100), thus relaxing the first-day cash constraint faced by released prisoners

[10] This was achieved by tracking every bus line going to Montevideo stopping at *ComCar* and plotting circles centered on each line's every stop with radii corresponding to the distance a prisoner could walk in the remaining time (assuming a maximum walking speed of four miles per hour). Then, if a prisoner took a bus at *ComCar* and got off thirty minutes later, he would have an hour left to walk, equal to a maximum of four miles in either direction.

and allowing us to explore the impact that this policy had on first-day recidivism.[11] The increase in the gratuity at released is indeed important: according to official statistics, it was 20 percent more than the amount of money needed to purchase a basic daily food basket. In purchasing power parity adjusted terms, the new gratuity at release is equivalent to more than three times the transfer given to a beneficiary of the program Bolsa Familia in Sao Paulo, Brazil (Chioda, De Mello, and Soares 2012), and more than five times the money received by a beneficiary of Familias en Acción in Bogota, Colombia (Camacho and Mejía 2013). In both cases, the cash transfer caused a significant decline in property crime.

We test for a discontinuous break in first-day recidivism associated with the September 5th 2010 increase in the gratuity at release. Important for our identification strategy, the increment in the gratuity is not correlated with any other policy or intervention that may also have had an effect on crime. In addition, there were no legal modifications affecting the level of punishment in the second semester of 2010.[12] In Table 6 we formally show that neither the number of releases nor the characteristics of the inmates released changed before and after September 5th 2010, thus providing further validity to the identification strategy.[13]

An anticipation of the impact of increasing the gratuity at release on first-day recidivism is shown in Figure 4. This figure presents the evolution of the coefficient corresponding to *Releases* obtained from a rolling regression (using a six-month window) of the specification in columns (3) and (4) in Table 7. We consider two symmetric periods around September 5th 2010: February 27th 2010 to September 5th 2010 and September 6th 2010 to March 15th 2011. Figure 2 shows that the

[11] The exchange rate of the Uruguayan Peso against the US Dollar was equal to 20.7 on September 6th 2010.
[12] If anything, the effective probability of apprehension decreased from 11.4 percent in 2009 to 10.8 percent in 2010. We estimate the probability of apprehension as the ratio of total prosecutions to total offenses after adjusting data on police-reported offenses for an underreporting rate of 50 percent (as suggested by victimization surveys).
[13] Given that there is no information available on the characteristics of the inmates released for the year 2011, we consider a symmetric window of 117 days before and after September 5th 2010.

coefficient on *Releases* is significantly higher in the period before the increased in the gratuity, presenting a sharp discontinuity on September 5th 2010.[14]

To formally address the impact of the increase in the gratuity on first-day recidivism, we estimate the effect of releases on total crime for the 360-day window before and after September 5th 2010. As shown in columns (1) and (2) in Table 7, the coefficient before the gratuity increase is bigger than the coefficient after the increase. The coefficients before and after the increase in the gratuity are significantly different from each other at the 10 percent level. The magnitude of the difference is important: the increase in the gratuity at release is associated with a decrease in first-day recidivism from 0.587 crimes per release to zero crimes per release.

We also explore the dynamics of first-day recidivism before and after September 5th 2010. As shown in columns (3) and (4) in Table 7, the correlation between crime and the number of inmates released is significant only for the same day of the release, and only for the period prior to the increase in the gratuity at release. When we include additional lags of *Releases* (up to t-7) all the coefficients are not significant (not reported), thus indicating that the increase in the stipend upon release is not displacing crime from the day of release to subsequent days.

Our results suggest the increase in the gratuity at release, a transfer equivalent to 120 percent of daily income, imply an income elasticity of -0.83. The income elasticity implicit in welfare programs in Brazil is -0.25 (Chioda, De Mello, and Soares 2012), in Colombia -0.4 (Camacho and Mejía 2013) and in the US -0.4 (Jacob and Ludwig 2010). The stronger effect we found is consistent with a higher propensity to commit crime in former inmates relative to welfare recipients.

The liquidity-constraint hypothesis

[14] This result is robust to alternative definitions of the window.

The liquidity-constraint hypothesis implies that first-day recidivism only affects property crime. As shown in Table 8, it does: the effect of releases comes exclusively from property crimes and for the period prior to the increase in the gratuity at release. In addition, the finding that first-day recidivism only affects property crime makes it unlikely that the ex-prisoners themselves could be victimized.

Another implication of the liquidity-constraint hypothesis is that first-day recidivism should affect more those released prisoners that are more constraint, such as the young and the single. As shown in Table 9, this is exactly what we find.

IV. Conclusions and discussion

This paper sheds new light on the behavior of criminals. We find the number of inmates released on any given day significantly affects the number of offenses committed that day, thus providing the first empirical evidence of first-day criminal recidivism. Our results are robust to a variety of alternative specifications, and they resist a Lasso-type selection procedure. The results not only are statistically significant, but also quantitatively important in terms of criminal behavior as the release of four prisoners leads to one more reported crime during the very day the prisoners are released.

We explore potential underlying reasons to our findings and provide evidence that first-day recidivism can be eliminated by an increase in the gratuity provided to prisoners at the time of their release. Even though the increase in the gratuity at release causes a huge reduction in crime at individual level, the reduction of aggregate crime (in Montevideo) is only 0.8 percent.

Our results have important policy implications by highlighting the importance of the amount of the gratuity at release when designing anti-crime policies. A simple cost-benefit analysis shows that increasing the gratuity at release is a very efficient policy. In our sample period, about 2,200 inmates are released from *ComCar* every year. According to our estimates, between 2004 and September 5^{th} 2010, on average, one out of four released prisoners reoffends the very day of the release, whereas this figure drops to zero after September 5^{th} 2010. This reduction in first-day recidivism costs $ 11,000 per year in gratuities at release, an amount that avoids 550 first-day reported offenses. Taking into consideration that public and private sector in Uruguay spend $ 4,000 to try to avoid each property crime (Aboal et al. 2013), the 2010 increase in the gratuity at release was a very efficient public policy from a cost-benefit perspective: each property offense avoided costs only 0.5 percent of the total expenditure in security.

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Table 1. Summary statistics

	Mean	Standard deviation	Observations
Total crime	270	33	2,631
Property crime	192	28	2,631
Non-property crime	78	14	2,631
Total crime 0-6hs	53	13	2,550
Total crime 6-12hs	62	12	2,550
Total crime 12-18hs	79	14	2,550
Total crime 18-24hs	77	13	2,550
Total crime within-range area	199	26	2,631
Total crime out-of-range area	70	12	2,631
Temperature (degree centigrade)	16.5	5.40	2,631
Rainfall (millimeters)	2.90	9.68	2,631
Holliday	0.04	0.19	2,631
Sunshine (hours)	7.27	4.05	2,631
Releases	5.92	6.49	2,631
Releases (less than 25 years old)	2.15	2.78	2,557
Releases (more than 25 years old)	3.64	4.02	2,557
Releases single	5.33	5.90	2,557
Releases married	0.64	1.06	2,557
Releases widowed	0.02	0.14	2,557
Releases theft	3.41	4.24	2,557
Releases robbery	0.68	1.10	2,557
Releases other crime	1.90	2.37	2,557

Note: Daily data for Montevideo for the period January 1st 2004 to March 15th 2011. For the variables Releases (less than 25 years old), Releases (more than 25 years old), Releases single, Releases married, Releases widowed, Releases theft, Releases robbery, Releases other crime, Total crime 0-6hs, 6-12hs, 12-18hs, and 18-24hs, the data is only available until December 30th 2010. The within-range area is made up of every jurisdiction a prisoner can easily access after release; the out-of-range area contains the remaining jurisdictions.

Table 2. Main results

	Dependent variable: Total crime							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Releases	0.225*	0.260**	0.259**	0.225**	0.234**	0.176*	0.202**	0.396***
	(0.124)	(0.123)	(0.123)	(0.096)	(0.096)	(0.100)	(0.100)	(0.130)
	{0.001}	{0.015}	{0.019}	{0.068}	{0.062}	{0.097}	**{**0.089**}**	{0.010}
Trend	-2.699***	-0.008***	-0.236***					
	(0.390)	(0.001)	(0.032)					
Temperature	0.720***	0.682***	0.682***	1.439***	1.438***	1.432***	1.426***	
	(0.170)	(0.168)	(0.168)	(0.159)	(0.159)	(0.177)	(0.177)	
Rainfall	-0.344***	-0.348***	-0.348***	-0.289***	-0.290***	-0.342***	-0.338***	
	(0.054)	(0.054)	(0.054)	(0.050)	(0.049)	(0.058)	(0.058)	
Holiday	-25.88***	-25.97***	-25.96***	-25.67***	-25.76***	-27.04***	-27.21***	
	(2.763)	(2.757)	(2.756)	(2.349)	(2.341)	(3.888)	(4.082)	
Sunshine	0.526***	0.540***	0.540***	0.960***	0.961***	0.883***	0.900***	
	(0.157)	(0.156)	(0.156)	(0.125)	(0.125)	(0.133)	(0.133)	
Day of the week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Year/month	No	No	No	Yes	Yes	Yes	Yes	
Observations	2,631	2,631	2,631	2,631	2,631	2,068	2,068	2,068

Notes: Newey-West heteroskedasticity- and autocorrelation- consistent standard errors (8 lags) are in parentheses. P-values (for the null hypothesis that the coefficient on Releases is equal to zero) obtained using the robust approach proposed by Canay, Romano, and Shaikh (2013) are shown in braces (10 clusters). All models are estimated by OLS and include a dummy for the 31st of December. A yearly trend is included in model (1), a daily trend in model (2), a monthly trend in model (3), and an intra-month daily trend in model (4). Model (5), our preferred specification, includes month/year combination dummies. Model (6) includes, as additional controls, the characteristics of the inmates released (proportion of releases by type of crime committed, age range, and marital status). Model (7) report estimates of Model (5) on the sample available in Model (6) (with inmate controls). Model (8) is obtained using a Lasso-type selection approach proposed by Belloni, Chernozhukov, and Hansen (2012). *Significant at 10 percent level. **Significant at 5 percent level. ***Significant at 1 percent level.

Table 3. Additional results

	Dependent variable: Total crime						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Releases	0.247**	0.221**	0.271**	0.163	0.202*	0.303***	-1.325
	(0.101)	(0.100)	(0.107)	(0.107)	(0.106)	(0.112)	(0.950)
Releases* Monday							1.749*
							(0.988)
Releases*Tuesday							1.443
							(0.978)
Releases*Wednesday							1.737*
							(0.964)
Releases*Thursday							1.626*
							(0.959)
Releases*Friday							1.425
							(0.965)
Releases*Sunday							-0.450
							(1.559)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of the week dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month combination	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,879	2,255	2,255	2,256	2,255	2,255	2,631

Notes: Newey-West heteroskedasticity- and autocorrelation- consistent standard errors (8 lags) are in parentheses. All models are estimated by OLS. Controls include rainfall, temperature, hours of sunshine, a dummy for holidays, and a dummy for the 31st of December. Model (2) excludes all Mondays from the sample. Model (3) excludes all Tuesdays from the sample. Model (4) excludes all Wednesdays from the sample. Model (5) excludes all Thursdays from the sample. Model (6) excludes all Fridays from the sample. *Significant at 10 percent level. **Significant at 5 percent level. ***Significant at 1 percent level.

Table 4. Dynamics

	Dependent variable: Total crime				
	(1)	(2)	(3)	(4)	(5)
Releases	0.244***	0.233**	0.241***	0.245***	0.233**
	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)
Releases in t-1	-0.052		-0.053	-0.084	
	(0.096)		(0.092)	(0.093)	
Releases in t-2			-0.031	-0.023	
			(0.087)	(0.087)	
Releases in t-3			-0.016	-0.014	
			(0.102)	(0.102)	
Releases in t-4			-0.004	-0.004	
			(0.092)	(0.092)	
Releases in t-5			0.046	0.052	
			(0.085)	(0.085)	
Releases in t-6			-0.111	-0.112	
			(0.091)	(0.091)	
Releases in t-7			0.034	0.038	
			(0.085)	(0.085)	
Accumulated					-0.019
Releases t-1 to t-7					(0.034)
Total crime in t-1		0.062***		0.063***	0.061***
		(0.020)		(0.020)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes
Day of the week dummies	Yes	Yes	Yes	Yes	Yes
Year/month combination dummies	Yes	Yes	Yes	Yes	Yes
Observations	2,630	2,630	2,624	2,624	2,624

Notes: Newey-West heteroskedasticity- and autocorrelation- consistent standard errors (8 lags) are in parentheses. All models are estimated by OLS. Controls include rainfall, temperature, hours of sunshine, a dummy for holidays, and a dummy for the 31st of December. **Significant at 5 percent level. ***Significant at 1 percent level.

Table 5. False experiments

	Dependent variable: Total crime						
		0-6hs	6-12hs	12-18hs	18-24hs	Within range area	Out of range area
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Releases	0.242***	0.040	0.141***	0.088*	-0.023	0.206***	0.044
	(0.097)	(0.040)	(0.042)	(0.046)	(0.043)	(0.082)	(0.036)
Releases in t-1	-0.053						
	(0.096)						
Releases in t+1	0.012						
	(0.082)						
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of the week dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month combination	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,629	2,550	2,550	2,550	2,550	2,631	2,631

Notes: Newey-West heteroskedasticity- and autocorrelation- consistent standard errors (8 lags) are in parentheses. All models are estimated by OLS. Controls include rainfall, temperature, hours of sunshine, a dummy for holidays, and a dummy for the 31st of December. The within-range area is made up of every jurisdiction a prisoner can easily access after release; the out-of-range area contains the remaining jurisdictions. *Significant at 10 percent level. ***Significant at 1 percent level.

Table 6. Differences in the characteristics of inmates released before and after September 5th 2010

		Before Sep 6th 2010	After Sep 5th 2010	Difference
Releases		6.564	7.496	0.932
		(0.594)	(0.718)	(0.932)
Crime Committed	Theft	3.538	3.846	0.308
		(0.397)	(0.405)	(0.567)
	Robbery	0.675	0.846	0.171
		(0.084)	(0.129)	(0.154)
	Other	2.350	2.803	0.453
		(0.230)	(0.291)	(0.371)
Age	18 – 24	2.060	2.179	0.120
		(0.248)	(0.275)	(0.370)
	25 +	4.333	5.068	0.735
		(0.377)	(0.483)	(0.612)
Marital Status	Single	6.239	6.974	0.735
		(0.573)	(0.662)	(0.876)
	Married	0.325	0.513	0.188
		(0.062)	(0.100)	(0.117)
	Widowed	0.000	0.009	0.009
		(0.000)	(0.009)	(0.009)

Notes: Standard errors are in parenthesis. Before September 6th 2010 is the mean of daily data from May 12th 2010 to September 5th 2010 (117 days). After September 5th 2010 is the mean of daily data from September 6th 2010 to December 31th 2010 (117 days).

Table 7. Impact of an increase in the gratuity received by inmates at release

	Dependent variable: Total crime			
	Until September 5^{th} 2010	After September 5^{th} 2010	Until September 5^{th} 2010	After September 5^{th} 2010
	(1)	(2)	(3)	(4)
Releases	0.587*	-0.120	0.522*	-0.040
	(0.306)	(0.236)	(0.313)	(0.248)
Releases in t-1			0.326	-0.177
			(0.302)	(0.277)
Total crime in t-1			-0.014	0.098
			(0.061)	(0.077)
Controls	Yes	Yes	Yes	Yes
Day of the week dummies	Yes	Yes	Yes	Yes
Year/month combination dummies	Yes	Yes	Yes	Yes
Observations	180	180	180	180

Notes: Newey-West heteroskedasticity- and autocorrelation- consistent standard errors (3 lags) are in parentheses. All models are estimated by OLS and use data for the 360-day window around September 5^{th} 2010. Controls include rainfall, temperature, hours of sunshine, and a dummy for holidays. *Significant at 10 percent level.

Table 8. Type of crime

	Until September 5^{th} 2010	After September 5^{th} 2010	Until September 5^{th} 2010	After September 5^{th} 2010
	Property		Non property	
	(1)	(2)	(3)	(4)
Releases	0.283***	0.008	-0.003	-0.108
	(0.084)	(0.200)	(0.046)	(0.120)
Controls	Yes	Yes	Yes	Yes
Day of the week dummies	Yes	Yes	Yes	Yes
Year/month combination dummies	Yes	Yes	Yes	Yes
Observations	2,440	191	2,440	191

Notes: Newey-West heteroskedasticity- and autocorrelation- consistent standard errors (8 lags) are in parentheses. All models are estimated by OLS. Controls include rainfall, temperature, hours of sunshine, a dummy for holidays, and a dummy for the 31^{st} of December. ***Significant at 1 percent level.

Table 9. Marital status and age

	Dependent variable: Total crime			
	(1)	(2)	(3)	(4)
Releases of single men	0.317***			
	(0.107)			
Releases of men that are not single		-0.452		
		(0.442)		
Releases (less than 25 years old)			0.624***	
			(0.207)	
Releases (more than 25 years old)				0.288*
				(0.149)
Controls	Yes	Yes	Yes	Yes
Day of the week dummies	Yes	Yes	Yes	Yes
Year/month combination dummies	Yes	Yes	Yes	Yes
Observations	2,557	2,557	2,557	2,557

Notes: Newey-West heteroskedasticity- and autocorrelation- consistent standard errors (8 lags) are in parentheses. All models are estimated by OLS. Controls include rainfall, temperature, hours of sunshine, a dummy for holidays, and a dummy for the 31st of December. *Significant at 10 percent level. ***Significant at 1 percent level.

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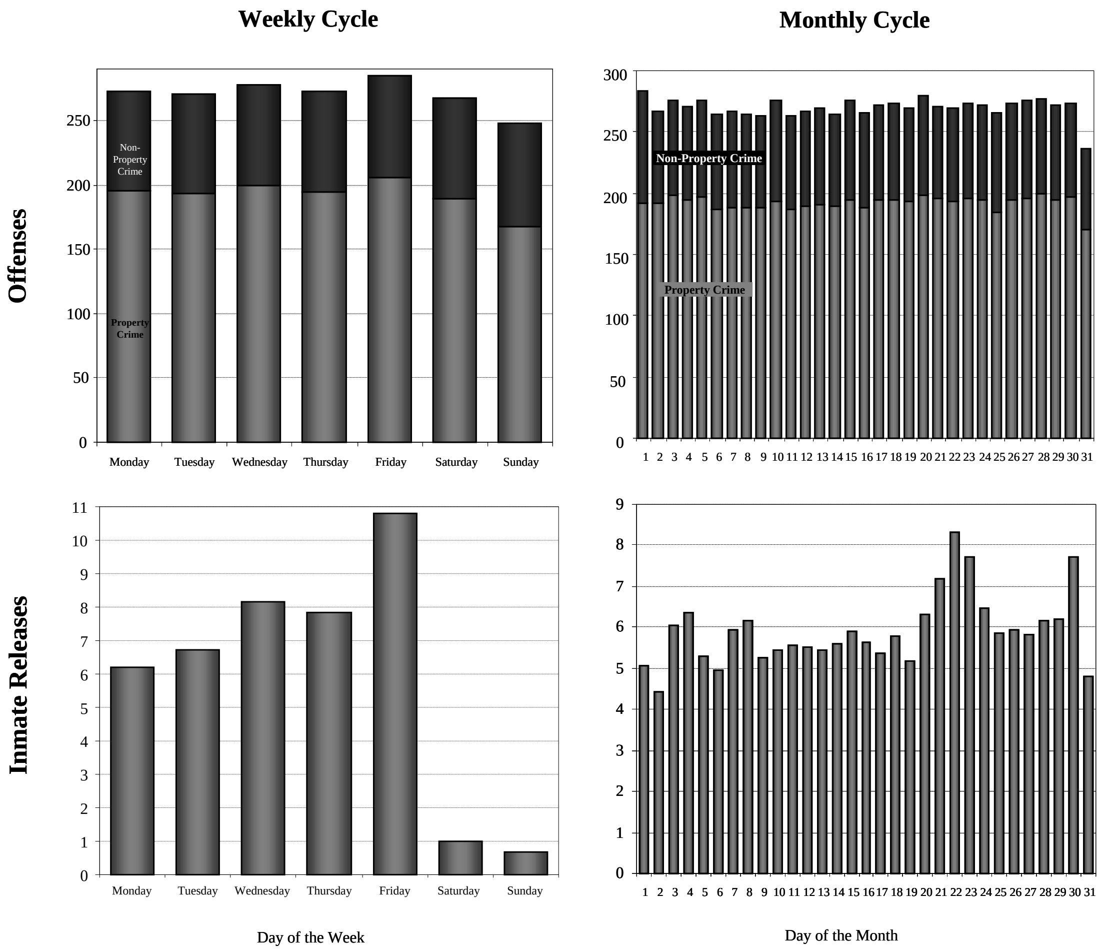
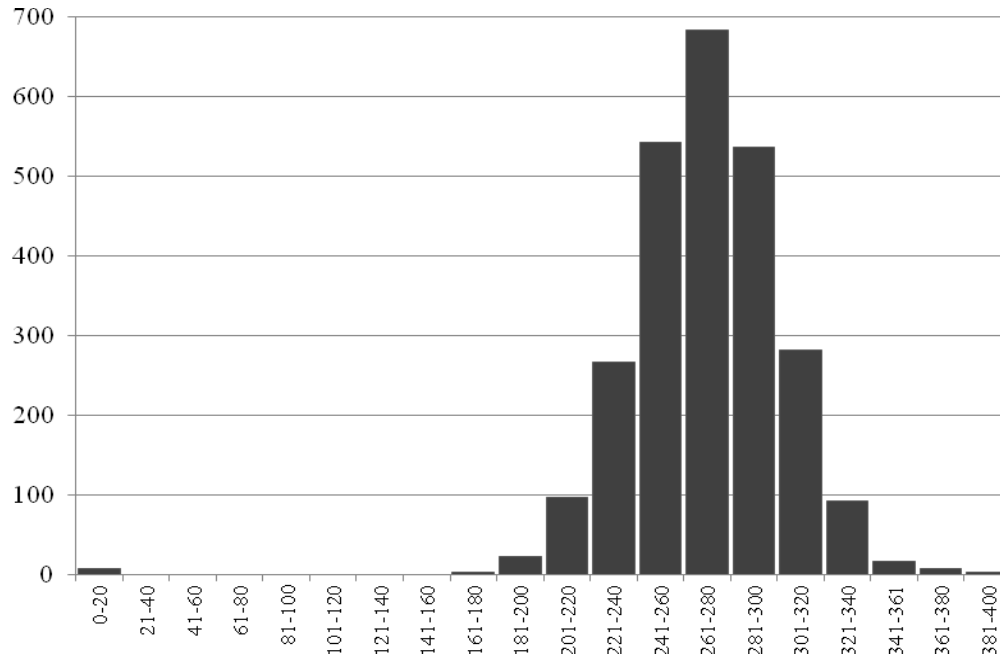
Figure 1. Weekly and Monthly Cycle of Releases and Offenses



Notes: The bars include sample average values. In the case of offenses, all the observations corresponding to December 31 were excluded from the average.

Figure 2. Histograms for Total crime and Releases

Total crime



Releases

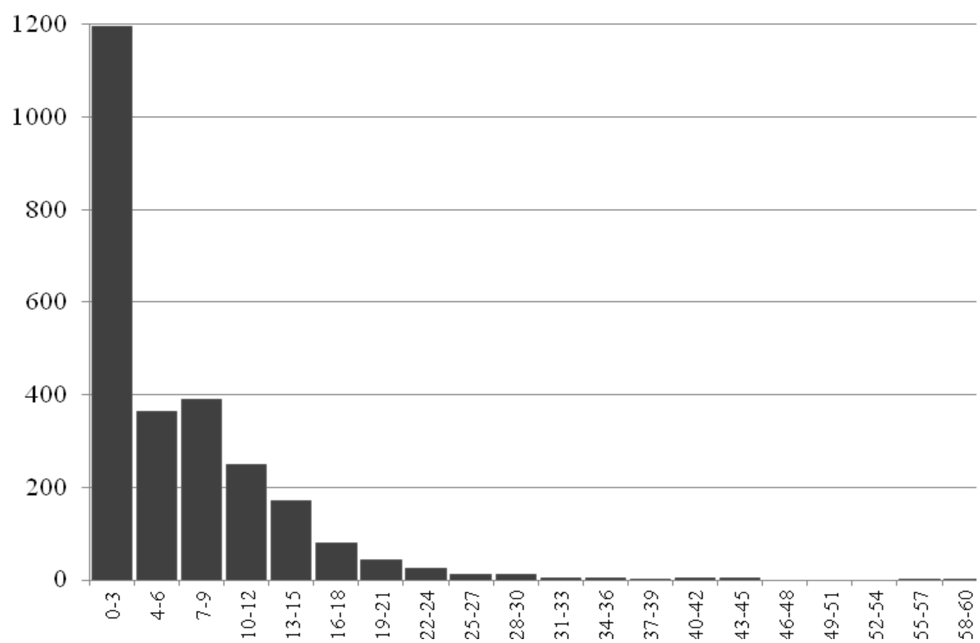
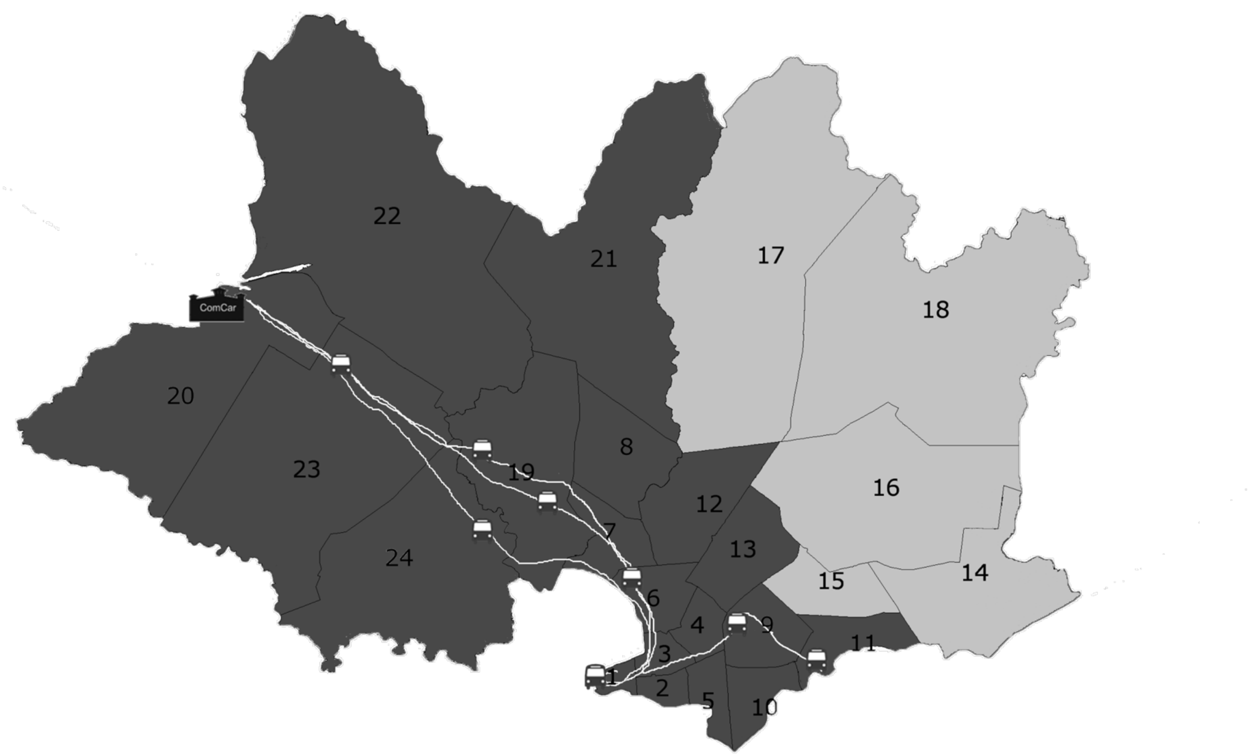
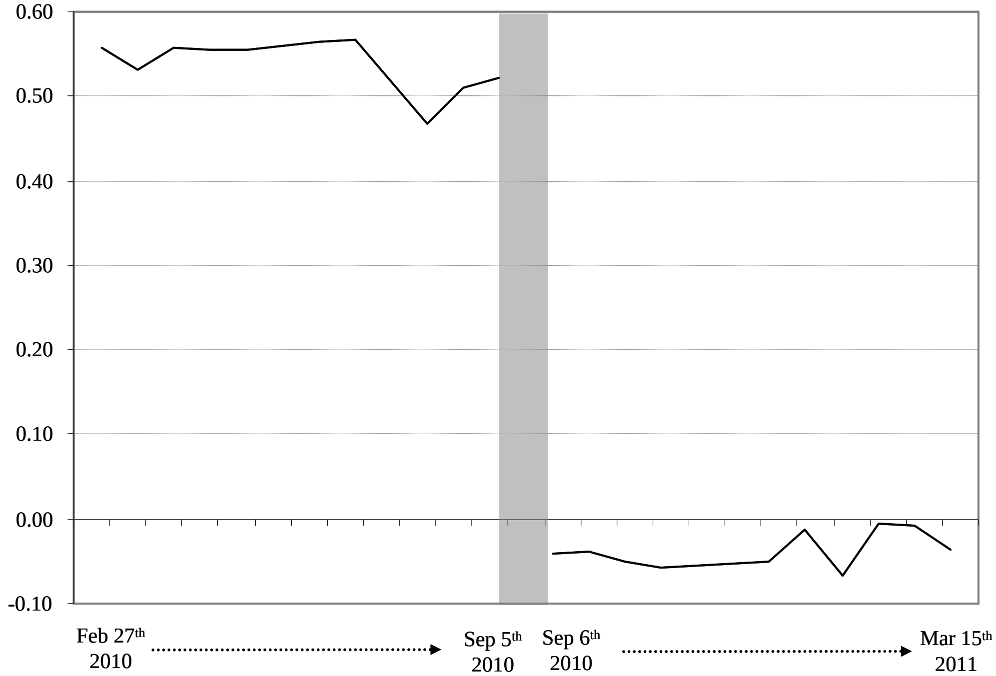


Figure 3: Within-range areas and out-of-range areas



Notes: The within-range area is made up of every jurisdiction a prisoner can easily access after release; the out-of-range area contains the remaining jurisdictions. Regions are determined by including all destinations a prisoner may reach on foot or by bus, within an estimated one and a half hour timeframe from leaving the prison. This was achieved by tracking every bus line going to Montevideo stopping at ComCar and plotting circles centered on each line's every stop with radii corresponding to the distance a prisoner could walk in the remaining time (assuming a maximum walking speed of four miles per hour).

Figure 4: Impact of an increase in the gratuity received by inmates at release on first-day recidivism



Notes: The figure shows the evolution of the coefficient corresponding to Releases obtained from a rolling regression (360-day window) of models (3) and (4) in Table 7. We consider two symmetric periods: February 27th 2010 to September 5th 2010 and September 6th 2010 to March 15th 2011.