Universidad de San Andrés

Doctorado en Economía

ESSAYS ON THE ECONOMICS OF CRIME

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CONTENTS

PREAMBLE

This dissertation consists of three essays on the Economics of Crime. In the first essay, I develop a new dynamic framework to analyze intertemporal issues of juvenile crime. In this model, the consistent decisions of forward-looking youths depend upon their work and crime related skills, which are shaped by their history of past choices. Significant changes in the incentives to engage in criminal activities couple with an unusual increase in juvenile crime make Uruguay an ideal environment to calibrate and test this model. Within this framework, I analyze the effectiveness of alternative policies in the fight against juvenile crime.

In the second essay, which is a joint work with Martín Rossi, we exploit a series of natural experiments to investigate the effect of frustration and euphoria on violent crime. Our results suggest that a fraction of crime against the property can be better characterized as a breakdown of control rather than a behavior driven by rational choice.

Finally, in the third essay, which is also a joint work with Martín Rossi, we shed 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. We explore potential underlying reasons to our findings and provide evidence consistent with the hypothesis that the driver of first-day recidivism is a liquidity constraint.

Acknowledgements

THE JUVENILE CRIME DILEMMA

Abstract

I develop a new dynamic framework to analyze juvenile crime. The consistent decisions, between crime and legal activities, of forward-looking youths depend upon their work and crime related skills, which in turn are shaped by their history of past choices. The model explicitly recognizes the contrasting levels of punishment of the juvenile and adult criminal systems. Significant changes in the incentives to engage in criminal activities coupled with an unusual increase in juvenile delinquency make Uruguay an ideal environment to calibrate and test this framework. Model predictions indicate that four factors can account for 86 percent of the observed variation in juvenile crime: the evolution of wages relative to the monetary gains from crime; a new lenient juvenile crime regulation that includes the decriminalization of attempted-theft; an increase in the escape rate from correctional facilities, and a cocaine base epidemic. Additional counterfactual results suggest an increase in the expected punishments of young offenders in the juvenile justice system is a better way to fight juvenile crime than an early transition to adult courts. The first alternative not only predicts a similar reduction in juvenile offending but also avoids negative consequences in terms of adult criminal behavior.

I. INTRODUCTION

Juvenile delinquency is at the forefront of social challenges worldwide. This concern cuts across economic development categories and geographical regions as youth crime rates are rising in virtually every part of the world (United Nations 2003). The delicate intersection between childhood and criminality creates a complex dilemma to deal with. Social scientists, activists, and legislators are all debating both the causes and potential solutions.[1]

The literature has found several determinants of juvenile criminal involvement.[2] Biological factors, such as being male, having low intelligence and short time horizons, are accurate predictors of crime. Family background factors, such as erratic parental discipline, lack of adequate supervision, and maternal rejection, are strongly correlated with later criminal involvement. Social factors, such as income inequality and marginalization, also exert significant influence on youth delinquent behavior. Since Becker (1968), juvenile delinquency can also be thought of as a rational response to the incentives for legal and criminal activities. Some youths will engage in criminal behavior if the potential gains are large enough while the expected punishment relatively low.

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[1] Juvenile offending covers a multitude of different violations of legal and social norms, ranging from minor offences to serious crimes committed by young people. The focus here is exclusively serious juvenile crime.

[2] See Levitt and Lochner (2000).

Juvenile crime is usually treated quite differently from adult crime. Offenses committed by minors are considered as delinquent acts within a separate juvenile justice system. This system is designed to recognize the special needs and immature status of adolescents while emphasizing rehabilitation over punishment. Juvenile criminal records are sealed from adult courts, arrested youths are judged by juvenile courts and once convicted are strictly segregated from adults in custody. Psychological research supports this dual treatment based on the psychosocial immaturity of adolescents (Steinberg 2009). However, in the fight against juvenile delinquency, several countries are considering trying violent juveniles as adults in court.

Beyond psychological concerns, invoking the heavy hand of the adult criminal justice system might also raise important issues of intertemporal choice and have ambiguous effects on the incentives for youth criminal involvement. The negative signal generated by court records, which ruins future wages, or the acquisition of criminal-specific human capital in detention centers could offset the potential reduction in juvenile crime achieved through deterrence after harsher punishments.

To tackle these issues, I develop a new dynamic model of crime in a framework where youths choose between crime and legal activities, and in which their work and crime related skills depend upon both their current and past choices. In this model, youths are forward-looking and so recognize their present choices affect their future skills and income. This approach incorporates individual heterogeneity since agents with different records face external incentives to crime in a different way and thus exhibit very different behavior.

Because the model developed in this paper is designed to explain juvenile crime, it accounts for the fact that key factors affecting individual decisions are significantly different before and after the age of majority (the age at which individuals become subject to adult courts). The probability of effective apprehension, punishment upon conviction, and evolution of work and crime related skills all vary depending on the individual's juvenile status.

This analysis differs from the models developed in the literature. In static models of crime agents make choices with no regard for future consequences of current decisions.[3] Previous dynamic models of crime develop significantly different frameworks from the model presented in this paper.[4] Only Mocan et al. (2005) explores a dynamic model of crime where agents are endowed with two types of human capital. Most importantly, to the best of my knowledge there are no previous theoretical models specifically designed to deal with juvenile crime.

Substantial changes in juvenile crime incentives make Uruguay an ideal environment to calibrate and test this model. The recent dynamics of wages and household wealth have led to financial rewards from criminal activities exceeding rewards in the job market. Additionally, the introduction of a more lenient juvenile crime regulation and control substantially lowered the expected cost of crime. As a result, juvenile crime almost tripled between 1997 and 2010. This massive spike in youth delinquency has triggered a strong debate over the threshold age of criminal responsibility. In fact, in 2014 Uruguayans will vote on whether to reform the

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[3]See Becker (1968), Ehrlich (1973), Block and Heineke (1975) and Witte (1980).

[4]See Flinn (1986), Imrohoroglu et al. (2004), Burdett et al. (2003), Burdett et al. (2004), Huang et al. (2004), Lochner (2004), Sickles and Williams (2008); and McCrary (2010) for a review of this literature.

Constitution in order to reduce the age of majority from 18 to 16 years of age.

The calibrated model is able to reproduce virtually all the recent increase in juvenile crime in Uruguay by affecting key model parameters in line with observed facts. The model predicts that the anemic evolution of wages relative to the monetary gains from crime (proxied by total per capita income) explains 35 percent of the variation in juvenile delinquency from 1997 to 2010. Additionally, a softer juvenile crime regulation approved in 2004, which includes the decriminalization of attempted-theft, plays a key role by explaining 38 percent of the observed variation. The significant increase in escapes from juvenile correctional facilities explains 13 percent of the actual increase in juvenile crime. Finally, the interaction of all the aforementioned facts with a reduction in the time horizons of youths, derived from a cocaine base epidemic, explains 86 percent of the observed spike in juvenile delinquency in Uruguay.

This result is consistent with the empirical literature suggesting that harsher punishments deter potential juvenile offenders (Levitt 1998; Imai and Krishna 2004; Mocan and Rees 2005; Oka 2009; Hjalmarsson 2009; Entoff 2011) and contradicts previous studies that find no evidence for such deterrence effects (Singer and McDowall 1988; Jensen and Metsger 1994; Steiner et al. 2006).

The model further provides a framework to quantify the effectiveness of alternative measures in the fight against juvenile crime. Counterfactual model results predict an early transition to adult courts would reduce juvenile delinquency by 35 percent due to the deterrent effects of harsher punishments. Alternatively, a harsher legal redefinition of juvenile offenses and the elimination of escapes from correctional facilities not only would reduce juvenile crime involvement by a similar magnitude but also would minimize the likelihood of criminal involvement later in life, once juveniles become adults.

Special care should be taken to segregate new inmates from experienced youth offenders in custody. If the school-of-crime effect, according to which inmates learn criminal skills in jail, were strong enough, the cure could prove worse than the disease, as the model predicts a harsher punishment could even increase juvenile crime rates.

The remainder of the chapter is organized as follows. Section II presents the model. Section III calibrates the model for Uruguay and section IV tests its ability to explain the recent juvenile crime spike. Section V analyzes alternative measures to fight juvenile crime. Section VI concludes.

II. THE MODEL

In this section, I develop a dynamic model to analyze juvenile behavior. Heterogeneous youths choose a strategy composed of an action for the current period and a set of actions for the subsequent periods of their working life, in order to maximize their discounted expected income: $E_t \sum_{t=0}^{T} \beta^t y_t$. E_t is the expectation operator conditioned on information available at time t, T is the age of retirement, β is the subjective discount factor, and y_t is the level of income at time t. Every period, individuals face both legal and criminal opportunities and choose between working or committing crimes. Agents are endowed with two different

types of skills, work-related skills H and crime-related skills B, which evolve based upon their choices.

If the agents decide to work, they accept one independent wage rate per unit of work-related skill w drawn from the time invariant distribution $F(w) = \Pr(w_t \leq w)$. Earnings in the period are the product of the wage rate offered and the agent's level of work-related skills. Working agents are then free to choose between work or crime the next period.

If the agents decide to engage in criminal activities, they run the risk of apprehension, which occurs with probability P. Detained agents are unable to realize the gains from crime. Agents who serve their prescribed sentences are convicted for s periods, which includes pre-trial detention time. Income is nil for the duration of the sentence and once released they will be able to choose again between work and crime. However, individuals are able to escape from detention centers with probability ε. Agents who escape from the detention center also receive zero income in the current period and are free to choose between work or crime the next period. The current income of those agents who engage in crime and evade police apprehension depends on the monetary gains from crime per unit of crime-related skills g and their level of crime-related skills. Those agents are then free to choose between work or crime the next period.

In all the cases, the continuation value next period depends upon whether the agents are in jail or free, and on how their work-related skills and crime-related skills evolved from the previous period.

Key factors affecting individual decisions are significantly different before and after the age of majority τ. The probability of apprehension, the probability of escape and the punishment once caught all vary with the individual's juvenile status.

Therefore, the value of the optimization problem for individuals with work-related skills H_t and crime-related skills B_t, who observe a realization of w_t at age t, is given by:

$$V(w_t, H_t, B_t, t) = \max_{\text{Work, Crime}} \left\{ \begin{array}{c} \underbrace{w_t H_t + \beta E_t V(w_{t+1}, H_{t+1}, B_{t+1}, t+1),}_{\text{Work}} \\ \underbrace{P_i (1 - \varepsilon_i) [\beta^{s_i} E_t V (w_{t+s_i}, H_{t+s_i}, B_{t+s_i}, t+s_i)]}_{\text{Crime + Sentence}} \\ \underbrace{+ P_i \varepsilon_i \beta E_t V (w_{t+1}, H_{t+1}, B_{t+1}, t+1)}_{\text{Crime + Escape}} \\ \underbrace{+ (1 - P_i) [g B_t + \beta E_t V (w_{t+1}, H_{t+1}, B_{t+1}, t+1)]}_{\text{Crime + Free}} \end{array} \right\} \tag{1}$$

$$\text{where } i = \left\{ \begin{array}{l} j \text{ (juvenile) for } t \text{ such that } 0 \leq t < \tau \\ a \text{ (adult) for } t \text{ such that } \tau \leq t \leq T \end{array} \right.$$

There are a finite number of both skill levels whose dynamics depend on the agent's choice. Table 1 depicts the laws of motion of state variables H_t and B_t. Work-related skills increase for individuals deciding to work due to on-the-job-training, leaving their level of crime-related skills unchanged. Agents deciding to engage in criminal activities who, after getting caught, serve their complete sentence imposed by the judge have their

work-related skills depreciate due to their criminal records and their crime-related skills increase due to both on-the-crime-training and the school-of-crime effect of conviction. Those individuals who manage to escape from the detention centers before serving their full sentence also face depreciation in their work-related skills and an increase in their crime-related skills through on-the-crime-training. Finally, agents who commit crime but remain free maintain the same level of work-related skills and observe an increase in their crime-related skills through on-the-crime-training.

Table 1. Law of Motion of Skills.

	$H_{t+1} =$	$B_{t+1} =$
Work	$H_t + \alpha_i$ with $\alpha_i > 0$	B_t
Crime + Sentence	$H_t - \eta_i$ with $\eta_i > 0$	$B_t + \gamma_i$ with $\gamma_i > 0$
Crime + Escape	$H_t - \eta_i$ with $\eta_i > 0$	$B_t + \chi_i$ with $\chi_i > 0$
Crime + Free	H_t	$B_t + \chi_i$ with $\chi_i > 0$

This endogenous evolution of skills recognizes both the stigmatization and the school-of-crime effects of incarceration. The stigmatization effect refers to the fact ex-offenders' earnings are low, even after controlling for their weak labor market characteristics (Western 2002; Holzer 2007). Incarceration erodes job skills and a criminal record signals to employers a potential employee might be untrustworthy. The belief that prisons are schools of crime also has widespread support. Empirical evidence suggests that confinement has negative consequences on future criminal behavior due to peer effects (Chen and Shapiro 2007; Camp and Gaes 2009). The intensity of both effects is different for juveniles and adults since juvenile records are usually sealed and convicted youths are strictly segregated from adults in custody.

Combining equation (1) with the laws of motion stated in Table 1, I get the following recursive formulation:

$$
V(w_t, H_t, B_t, t) = \max_{\text{work, crime}} \left\{
\begin{array}{c}
w_t H_t + \beta \int_{w_{t+1}} V(w_{t+1}, H_t + \alpha_i, B_t, t+1) dF(w_{t+1}), \\
P_i (1 - \varepsilon_i) \left[\beta^{s_i} \int_{w_{t+s_i}} V(w_{t+s_i}, H_{t-s_i} - s_i \eta_i, B_{t-s_i} + s_i \gamma_i, t + s_i) dF(w_{t+s_i}) \right] \\
+ P_i \varepsilon_i \left[\beta \int_{w_{t+1}} V(w_{t+1}, H_t - \eta_i, B_t + \chi_i, t+1) dF(w_{t+1}) \right] \\
+ (1 - P_i) \left[g B_t + \beta \int_{w_{t+1}} V(w_{t+1}, H_t, B_t + \chi_i, t+1) dF(w_{t+1}) \right]
\end{array}
\right\}
\tag{2}
$$

where dF denotes the probability density function of the wage rate per unit of work-related skill.

Equilibrium Dynamics

Assuming no population growth, I obtain the equilibrium dynamic behavior by solving the problem through backward induction, starting from the last period of the agents' working lives.

Let $C(w_t, H, B, t) = 1$ if the agents in state (w_t, H, B, t) commit crime and let $C(w_t, H, B, t) = 0$ otherwise. Then, $J(w_t, H, B, t)$ is the number of free juveniles with work-related skills H and crime-related skills B facing w_t at age t conditional on a given history of realizations of w, and evolving according to the following recursive equation:

$$
\begin{aligned}
J(w_t, H, B, t) = {} & [1 - C(w_{t-1}, H - \alpha_j, B, t - 1)] J(w_{t-1}, H - \alpha_j, B, t - 1) \\
& + \begin{bmatrix} P_j(1 - \varepsilon_j) C(w_{t-1-s_j}, H + s_j\eta_j, B - s_j\gamma_j, t - s_j) \\ J(w_{t-1-s_j}, H + s_j\eta_j, B - s_j\gamma_j, t - s_j) \end{bmatrix} \\
& + P_j\varepsilon_j C(w_{t-1}, H + \eta_j, B - \chi_j, t - 1) J(w_{t-1}, H + \eta_j, B - \chi_j, t - 1) \\
& + (1 - P_j) C(w_{t-1}, H, B - \chi_j, t - 1) J(w_{t-1}, H, B - \chi_j, t - 1)
\end{aligned} \tag{3}
$$

The first addend on the right hand side of the equation (3) denotes the number of juveniles with work-related skills $H - \alpha_j$ and crime-related skills B who faced a wage w_{t-1} and decided to work at $t - 1$. The second addend represents those convicted juveniles with work-related skills $H + s_j\eta_j$, crime-related skills $B - s_j\gamma_j$, who faced wage w_{t-1-s_j}, committed crime at $t - 1 - s_j$, and are free by t according to their sentence length. The third addend represents those youths with work-related skills $H + \eta_j$ and crime-related skills $B - \chi_j$ who faced wage w_{t-1}, committed crime at $t - 1$, and after getting caught immediately escaped from the detention center. Finally, the last addend represents those juveniles with work-related skills H and crime-related skills $B - \chi_j$ who faced wage w_{t-1}, committed crime at $t - 1$ and avoided getting caught by the police.

Therefore, the total number of minors that commit crime is given by:

$$
JC = \int_w \sum_H \sum_B \sum_{t=0}^{\tau-1} J(w_t, H, B, t) C(w_t, H, B, t) \, dF(w_t) \tag{4}
$$

Equation (4) tracks only changes in the number of active offenders, not the total number of crimes committed. However, given that the literature has typically found a constant offending rate of active offenders at any given age (Loeber and Snyder 1990), the relative change in JC in a given period should account for the total variation in juvenile offending in such a period.[5]

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[5] A shortcoming of the analysis is the potential instability of the offending rate of active offenders (the so-called lambda in the literature). This is relevant for section V since it could be argued that a constant lambda through time is no longer true when analyzing significant changes in policy.

III. CALIBRATION

In this section I calibrate the model to fit the juvenile crime rates observed in Uruguay in 1997, before the beginning of the economic crisis and the introduction of relevant changes to the juvenile crime laws.

Each time period is a quarter and agents live for 200 quarters, or 50 years. I fix the discount factor β to 0.986, or just under 6 percent annually. Because the decisions makers are youths, this shorter than usual time horizon is consistent with the evidence that concern about the future and ability to plan ahead increase across the lifespan (Nurmi 1991; Green et al. 1994; Green et al. 1996; Green et al. 1999; Steinberg et al. 2009).

Table 2 depicts estimates of the key security parameters before and after the age of majority (applicable to Uruguay in 1997).

Table 2. Public Security Parameters (1997).

	Parameter	Juveniles ($i = j$)	Adults ($i = a$)
P_i	Probability of Apprehension	10%	10%
s_i	Average Sentence Length	2Q	5Q
ε_i	Probability of Escape	11%	0

I estimate the probability of apprehension as the ratio of total prosecutions to total offenses after adjusting data on police-recorded offenses for an underreporting rate of 60 percent.[6] This probability is 10 percent for both juveniles and adults. I then estimate an average adult sentence length of 5 quarters using the complete distribution of the effective duration of the prison spell of a representative sample of the Uruguayan prison population.[7] Information on effective sentence lengths is not available for juveniles. However, Uruguayan juvenile crime specialists state that the effective average sentence length for juveniles was about 2 quarters in 1997. I define the probability of escape as the ratio between number of prison breaks and total number of inmates, which differs before and after the age of majority. According to official statistics, this probability was 0.4 percent for adults and 11 percent for youths.

I set 135 different skill levels evenly partitioning the interval $[1, 2]$. Someone who starts out working with the lowest skill level will reach the highest level after 25 years, conditional on working in every period. I estimate the initial distribution of work-related skills through the results of the 2003 OECD Programme for International Student Assessment (PISA).[8] By design, PISA test scores reflect the aptitude for the job

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[6]The underreporting rate, which is in line with the rate estimated for the U.S. (Levitt 1996) and for Chile (Nuñez at al. 2003), was computed considering government estimates (Universidad de la República 2011) and own calculations based on victimization surveys (Latin American Public Opinion Project -Vanderbilt University 2010).

[7]I consider the data of the complete history of entries and exits from penitentiary center ComCar (Complejo Carcelario Santiago Vázquez) since 2002. According to Prisoner Ombudsman Alvaro Garcé, inmates in ComCar (35 percent of the prison population) are a representative sample of urban Uruguayan offenders.

[8]The first participation of Uruguay in PISA was in 2003.

market for a representative sample of Uruguayan youths. Due to lack of information, I assume a uniform distribution of crime-related skills.[9]

The annual variation in both skill levels is set in Table 3. If the individuals decide to work, their work-related skills increase by 0.0075 units in the interval $[1, 2]$. Put differently, the annual growth rate of work-related skills ranges from 3.2 percent at the lowest skill levels to 1.6 at the highest skill levels, in line with estimates for Uruguay (Sanroman 2006). Agents who have reached the highest work-related skill levels retain those skills until committing crime or retiring. Crime-related skills remain constant. If the agents commit crime and remain free, their crime-related skills increase due to on-the-crime-training by 0.0075 units in the interval $[1, 2]$. Agents who have reached the highest crime-related-skill levels retain those skills until working again. Work-related skills remain constant. The impact on skills is significantly different for adults and juveniles if the police catch them. If the agents are apprehended but manage to escape, the reduction in work-related skills is five times worse for adults than for juveniles since the stigmatization effect is higher after reaching majority (Allgood et al. 2003). The impact on crime-related skills is the same for both adults and juveniles due to similar on-the-crime-training. Finally, if agents are apprehended after crime and serve the complete sentence, the reduction in work-related skills and the increase in crime-related skills are five times higher in the case of adults as the stigmatization effect is higher and the school-of-crime effect is stronger with more experienced teachers.

Table 3. Skill Parameters.

	Work-Related Skills (H)			Crime-Related Skills (B)		
	Parameter	Juveniles	Adults	Parameter	Juveniles	Adults
Work	α_i	0.0075	0.0075	—	—	—
Crime + Sentece	η_i	0.0075	0.0375	γ_i	0.0075	0.0375
Crime + Escape	η_i	0.0075	0.0375	χ_i	0.0075	0.0075
Crime + Free	—	—	—	χ_i	0.0075	0.0075

Data from the national household survey of Uruguay suggests the wage rate per unit of education (years of schooling) follows a lognormal distribution with a mean very close to the standard deviation. Thus, I assume that the wage rate per unit of work-related skill is drawn from a lognormal distribution with mean and standard deviation $\overline{w}$.

Finally, I calibrate the only free parameter of the model, the time invariant mean wage per unit of work-related skill relative to the monetary gain per unit of crime-related skill $\overline{w}/g$, to reproduce the observed juvenile crime rate in Uruguay in 1997.[10]

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[9] Considering potential learning of crime-related skills at home, I assume that the initial distribution of crime-related skills follows the results of PISA test scores. I then reproduce sections 4 and 5 without substantial changes (results available upon request) .

[10] I assume that only a minority of those youths with high incentives for crime actually engage in crime. Empirical evidence

IV. AN INCENTIVE-COMPATIBLE INCREASE IN JUVENILE CRIME

Juvenile crime rates have risen at a striking rate over the past fifteen years in Uruguay. Between 1995 and 2006, the number of robberies committed by juveniles increased almost three times more than those committed by adults. In 2010, minors aged 13-17 comprised roughly 8 percent of the overall population, but accounted for 26 percent of the homicides and more than 40 percent of the total number of robberies (Bonomi 2011). Criminal court records indicate that youth crime increased 180 percent between 1997 and 2010 (Poder Judicial 1999-2010).[11]

To test the model's ability to reproduce actual juvenile crime variation in Uruguay I start with the model calibrated to match 1997 juvenile crime rates. I then exogenously affect key model parameters in order to reflect the economic and institutional changes observed in Uruguay. The low increase in wages relative to the increase in monetary gains from crime, the introduction of a laxer juvenile crime regulation, the increase in the breakout rate from correctional facilities, and the cocaine base epidemic are all relevant factors to analyze. For each factor, I compute the model predicted increase of juvenile crime (consistent with the changes observed in Uruguay). Finally, I compare the model prediction and the actual change observed between 1997 and 2010. Table 4 presents the results.

Table 4. Factors Affecting Juvenile Crime's Dynamics.[12]

		(1)	(2)	(3)	(4)	(5)	(6)
Parameter	Baseline	Wages/Loot	Juv. Code	(1) + (2)	Breakouts	(3) + (4)	(5) + Drugs
$\overline{w}/g$	1.4	**1.4/1.2**	1.4	**1.4/1.2**	1.4	**1.4/1.2**	**1.4/1.2**
P_j	10%	10%	**6%**	**6%**	10%	**6%**	**6%**
s_j	2	2	**1**	**1**	2	**1**	**1**
ε_j	11%	11%	11%	11%	**38%**	**38%**	**38%**
β	0.986	0.986	0.986	0.986	0.986	0.986	**0.981**
Increase in Juv. Crime		63%	69%	118%	21%	136%	155%
% of Actual Increase		35%	38%	65%	13%	75%	86%

Note: The affected parameter in each model intervention is printed in bold.

suggests 13 percent of individuals engage in profitable illegal activities even when their actions could not be witnessed (Levitt and Dubner 2005).

[11]Raw data from criminal court records indicate that youth crime increased 110 percent in 2010 relative to the levels observed in 1997 (Poder Judicial 1999-2010). However, these records understate the rise in juvenile crime as attempted-theft (one of the most common types of juvenile offense in Uruguay) was decriminalized in the juvenile crime code passed in 2004. Before the introduction of this new regulation, attempted-theft represented 25 percent of the total number of trials initiated by the juvenile justice system (Sayagués-Laso 2004 and 2010). I thus adjust the number of procedures initiated by the juvenile justice system between 2004 and 2010 by a factor of 4/3 to provide a consistent time series of juvenile offending that accounts for attempted-thefts.

[12]Matlab codes available upon request.

Both wages and total per capita income fell dramatically during the 1998-2002 economic crisis in Uruguay and then began to recover. However, while in 2010 real per capita income was 34 percent above its 1997 level, real private wages were only 12 percent above pre-crisis peak. This observed gap between wages and per capita income affects the individual return to crime if monetary gains from crime per unit of crime-related skills increase hand in hand with per capita income. To assume that the loot increases with income is frequent in the literature (Ehrlich 1996) and in line with the empirical evidence from police records on property crime in Uruguay.[13] In other words, the financial rewards from criminal activities increased 20 percent more than the financial rewards from legal work. Therefore, when I affect the model parameter $\overline{w}/g$ to reproduce the observed dynamics in per capita income and wages, the model predicts an increase in juvenile crime of 63 percent, which accounts for 35 percent of the total observed variation (see column (1) of Table 4).

The calibrated model is also able to reproduce the evolution of adult crime over the same period after the adjustment in $\overline{w}/g$.[14] The model predicts an increase of 113 percent in adult crime whereas the number of criminal procedures (per 100,000 adults) initiated by the adult criminal justice system increased by 108 between 1997 and 2010 (Poder Judicial 1999-2010). Predictions on adult crime provide an out-of-sample test for the model, as it was not initially calibrated to match adult crime.

Figure 1 illustrates juveniles' incentives to either commit crime or to work as a function of both skill levels: the higher (lower) the work-related skills and the lower (higher) the crime-related skills, the larger (smaller) the region where incentives to work are stronger than those to commit crime. Given the observed evolution of per capita income and wages, the shaded critical area, denoting the combination of skills that make it profitable to engage in criminal activities, expands from 0.02 percent to 7.8 percent of the total area. Additionally, the number of youths with the combination of skills that make crime profitable increases over time, as criminal activity increases crime-related skills and decreases work-related skills.

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[13]According to police records on property crimes, seven categories comprise 70 percent of all stolen property in a quite stable pattern for the analyzed time period. Among these categories, 75 percent is represented by electronics and appliances (22-24%), clothing and accessories (7-9%), jewelry (4-5%), cars (3-6%), bicycles (2-5%) and construction tools (3-4%). The pecuniary returns from crime associated with these categories are naturally assumed to move with per capita income. The remaining 25 percent of total stolen property is comprised of money, which I also assumed to evolve along per capita income since there is no evidence of significant deepening bancarization (decreased use of cash) in Uruguay. As a matter of fact, Uruguayans' bank deposits over GDP and bank credit over GDP in 2010 were nearly identical to those observed in 1997.

[14]The variation in adult crime is given by the change in $\int_w \sum_H \sum_B \sum_{t=\tau}^{T} J(w_t, H, B, t) C(w_t, H, B, t) \, dF(w_t)$.

Figure 1. Skills and Incentive Regions.
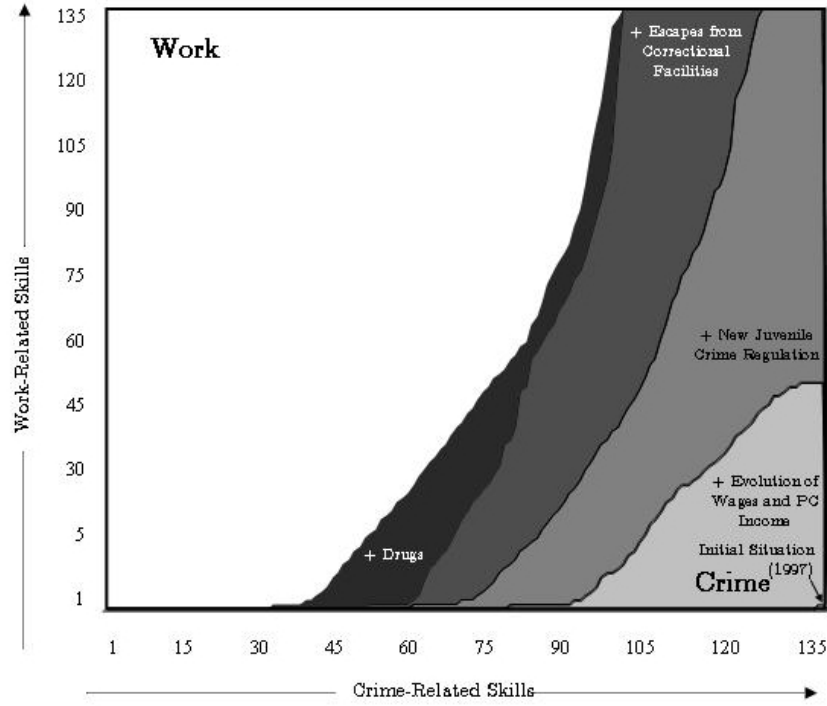
The second factor I examine is the approval of a lenient juvenile criminal code (Law 17,823) in 2004. Beyond several changes in procedures dealing with juveniles, the new code decriminalized attempted-theft and established that judges should not consider aggravating circumstances for offenses committed by minors.[15] According to specialists, this new juvenile regulation implied a reduction by about 50 percent in the average sentence length.[16] Additionally, the 2004 code allowed judges to arbitrarily decide whether to even initiate a judicial procedure. In fact, during the first year under the new code, judges decided to release 40 percent of the juveniles under suspicion (Sayagués-Laso 2004). After modifying the average sentence length s_j and the probability of apprehension P_j consistently with the new code, the model predicts an equilibrium increase in juvenile crime of 69 percent relative to 1997 (see column (2) of Table 4).

When I combine this legal modification with the observed differential evolution of the return of legal and criminal activities, the model predicts an increase in youth delinquency of 118 percent, accounting for 65 percent of the observed variation in juvenile offending (see column (3) of Table 4). Again, the region of skills for which incentives to engage in crime are higher than those to work expands significantly to reach 24 percent of the total area (see Figure 1).

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[15] Attempted-theft applies when offenders are arrested in the act of theft or right after committing theft while still in possession of the stolen property, and is defined as a crime for adults.

[16] According to members of the Supreme Court of Justice, juveniles are currently punished with sentences that are only 1/6 of those applicable to adults for the same type of offense.

The third factor I consider to explain the evolution of juvenile delinquency in Uruguay is the rise in the escape rate from correctional facilities. In fact, according to official statistics and expert opinions, the probability of escape from detention centers ε_j jumps from 11 percent in 1997 to 38 percent in 2010. After changing the escape probability in line with the evidence, the model predicts an equilibrium increase of 21 percent in juvenile crime relative to 1997 (see column (4) of Table 4). Moreover, after considering the last three factors together, the model explains 75 percent of the juvenile crime increase observed in Uruguay (see column (5) of Table 4). A new expansion that reaches 40 percent of the total area of the critical region of skills where the incentives to commit crime are stronger than those to work lies behind such a significant increase in juvenile delinquency (see Figure 1).

Finally, I introduce a fourth factor into the analysis: the cocaine base epidemic. The incidence of cocaine base among adolescents has skyrocketed in Uruguay since 2003. Official statistics indicate that cocaine base seizures multiplied by 6.8 between 2003 and 2010, while total annual drug seizures multiplied by only 1.5 (Junta Nacional de Drogas 2010a). In fact, 10 percent of the juvenile population from backgrounds with high social vulnerability frequently consumes cocaine base (Junta Nacional de Drogas 2007) and cocaine base incidence among inmates in juvenile correctional facilities is 53 percent (Junta Nacional de Drogas 2010b). Becker and Mulligan (1997) develop a theoretical model in which drug addiction causes a rational increase in future discounting. Moreover, experimental studies show that drug consumption increases discount rates by a factor close to five (Bretteville-Jensen 1999; Petry 2003; Coffey et al. 2003; Kirby and Petry 2004). To recognize this change in the capacity to project events into the future in the target population, I exogenously reduce the value of parameter β from 0.986 to 0.981.

All four factors together: the evolution of the return to legal activities below monetary gains from crime, the lenient juvenile crime regulation, the escapes from correctional facilities and the cocaine base epidemic are able to explain 86 percent of the observed variation in youth delinquency (see column (6) of Table 4). The critical region of skills in which the incentives to commit crime are stronger than those to work expands to 44 percent to the total area (see Figure 1). This, combined with a new increase in the number of free youths endowed with such skills combinations produce the predicted increase in juvenile offending.

Moreover, if I consider the observed dynamics of each of these key factors affecting youth's decisions year by year, the model almost replicates the actual time series of juvenile crime in Uruguay (see Figure 2).[17]

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[17]To compute the time series of the key factors affecting juvenile crime, I proceed as follows. Real wages and per capita income evolve according to official statistics. I think in two periods in order to compute the time series of the probability of apprehension and the average sentence length facing youths. Between 1997 and 2003, I consider constant values at pre-new-juvenile-crime-regulation levels. Between 2004 and 2010, I consider constant values consistent with the new juvenile crime code. I compute the time series of the probability of escape between 2005 and 2010 with available official data. Due to lack of information, I have to impute to the period 1997-2004 the observed value in 2005. Finally, I extrapolate the evolution of the discount factor considering the observed variation in cocaine base seizures.

Figure 2. Evolution of Juvenile Crime.
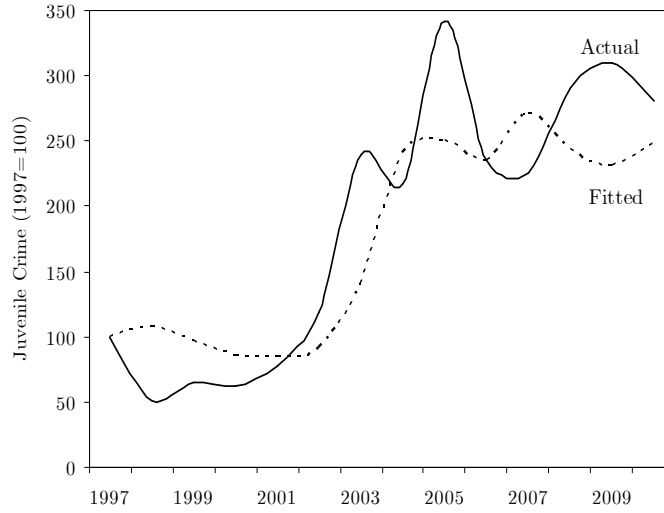
To sum up, I virtually reproduce the evolution of juvenile delinquency in Uruguay from 1997 to 2010 by affecting only key model parameters according to actual changes. Thus, a model in which youths rationally respond to observed increases in the financial rewards from crime and to significant reductions in the expected punishment can explain the growth in juvenile crime in Uruguay. Model results suggest the current juvenile crime rates in Uruguay are not so surprising after all. Economic and institutional factors are conducive to an environment where a significant fraction of the youth population is at the margin of choosing whether or not to engage in criminal activities. In the same vain, it should come as no surprise either that records on judicial interviews with adolescents reveal more than 50 percent of youths involved in criminal activities in Uruguay state delinquency as their professional activity (Sayagués-Laso 2010).

V. THE FIGHT AGAINST JUVENILE CRIME

In this section, I use the already calibrated and tested model to perform counterfactual exercises in order to analyze the effectiveness of alternative policies in the fight against juvenile crime.

I first adjust the initial parameterization to reproduce 2010 situation in Uruguay. Both labor income and the monetary gains from crime have to reflect the observed gap in the evolution of wages and per capita income ($\overline{w}/g = 1.4/1.2$). For juveniles, the new probability of effective apprehension ($P_j = 6\%$), the new average sentence length ($\overline{s}_j = 1$) and the new probability of escape ($\varepsilon_j = 38\%$) have to reflect a more lenient expected punishment for potential offenders. The current discount factor ($\beta = 0.981$) has to be consistent with the cocaine base incidence among juveniles in Uruguay. According to the national household survey, the distribution of wages per unit of work-related skill in 2010 mirrors the pattern observed in the 1997 calibration. The same is true for the initial distribution of work-related skills of the juvenile population which I now estimate using the results of the 2009 PISA tests.

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A consensual way to fight juvenile delinquency is by increasing the opportunity cost of crime through the improvement of work-related skills and wage rates. In fact, recent empirical literature strongly supports the negative relationship between education and crime (Machin et al. 2012; Meghir et al. 2012). In this line, the model predicts that if Uruguayan youths had the work-related skills observed in Finland (one of the world's leaders in youth academic performance according to the PISA tests, see Figure 3) and if the wage rate per unit of work-related skill recovered its relative levels with respect to per capita income observed in 1997, juvenile crime would decline by 50 percent.

Figure 3. Work-Related-Skills Distribution.
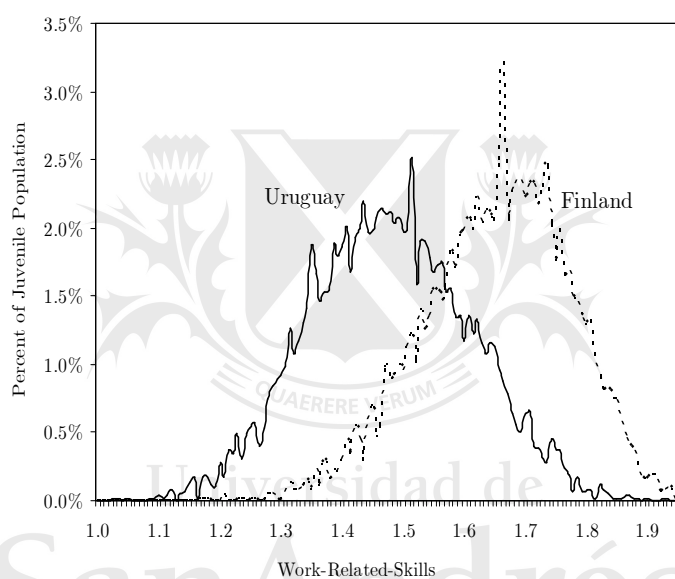
Under this scenario, legal activities would become more attractive than crime for a large set of Uruguayan youths. However, it would require a deep reform in the Uruguayan education system to significantly reduce the number of juveniles without the minimum requirements for productive insertion in the labor market. 2009 PISA results indicate educational failure should be reduced from the current 44 percent to the 7 percent observed in Finland.

Alternative policies aimed at reducing the gains from crime by increasing the potential punishment facing youths should thus be considered. I first evaluate the effects to partially eliminate the separate juvenile justice system, treating some adolescents by adult standards of criminal culpability and punishment. Early transition to adult courts implies key adult security parameters as well as adult levels of stigmatization and school-of-crime effects apply to those juveniles aged 16-17 (see Table 5). If those aged 16-17 face a probability of apprehension of 10 percent instead of 6 percent, an average sentence length of 5 quarters instead of 1 quarter and a nil probability to escape from detention centers instead of 38 percent, the model predicts a

reduction a 35 percent reduction in youth delinquency.[18] The deterrence argument that harsh punishments reduce criminal involvement holds once the age of majority is reduced.[19]

Table 5. Increase in the Expected Punishment of Juveniles.

| | Early Transition to Adult Courts | | | | Harsher Juv. System | |
| Model | 13-15 ys | | 16-17 ys | | 13-17 ys | |
Parameter	Baseline	Policy	Baseline	Policy	Baseline	Policy
P_j	6%	6%	6%	**10%**	6%	**10%**
s_j	1Q	1Q	1Q	**5Q**	1Q	**2Q**
ε_j	38%	38%	38%	**0%**	38%	**0%**
η_j	0.0075	0.0075	0.0075	**0.0375**	0.0075	0.0075
γ_j	0.0075	0.0075	0.0075	**0.0375**	0.0075	0.0075

Note: The affected parameter in each model intervention is printed in bold.

I alternatively evaluate measures that would imply harsher expected punishment for juveniles but maintain the trying of minors in juvenile courts (see Table 5). For starters, it implies the complete elimination of escapes from youth detention centers thanks to tighter security measures. This measure should be complemented with a legal redefinition that increases the average sentence length from 1 quarter to 2 quarters and the effective probability of apprehension from 6 percent to 10 percent (the levels observed before the 2004 juvenile crime code). According to model estimates, this harsher juvenile crime system would reduce youth crime by 36 percent.

Both the reduction of the age of majority and the increase in the expected punishment in the juvenile system predict a similar reduction in youth crime. However, model results suggest opposite effects on criminal involvement once current juveniles become adults.[20] While the increase in the expected level of punishment in the juvenile system reduces future adult crime by 10 percent, an early transition to adult courts increases the incentives for crime later in life as adult crime increases by 5 percent. The stigmatizing treatment in adult courts coupled with the acceleration in the transmission of crime-related skills in adult detention facilities offset the deterrent effect brought about by the harsher punishment, generating incentives for future criminal involvement. This result is consistent with the empirical evidence that suggest trying and sentencing juvenile offenders as adults increases the likelihood of recidivism (Podkopacz and Feld 1995; Bishop et al. 1996; Fagan 1996; Myers 2003).

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[18] Matlab codes available upon request.

[19] In fact, some lab experiments suggests that only strong punishments deter crime (Schildberg-Hörisch and Strassmair 2010).

[20] To compute the variation in adult crime, I consider the expected behavior of current youths at early adulthood (18-27 years old) according to the following formula $\int_w \sum_H \sum_B \sum_{t=\tau}^{\tau+10} J(w_t, H, B, t) C(w_t, H, B, t) dF(w_t)$.

Rehabilitation of youth offenders should thus be the first order of business. Rehabilitation could be consistent with a longer sentence if it enhances work-related skills. However, if the increase in crime-related skill in correctional facilities were strong enough, the model suggests that longer sentences, under either the adult or juvenile system, could even increase juvenile crime rates.

VI. CONCLUSIONS AND DISCUSSION

Psychological literature has long recognized that psychosocial maturation proceeds more slowly than cognitive development and that age differences in judgment reflect social and emotional differences between adolescents and adults. These differences are exacerbated in aspects such as susceptibility to peer influence, future orientation, reward sensitivity and the capacity for self-regulation (Steinberg 2009). However, a rational model of youth behavior, where consistent decisions after changes in the incentives of forward-looking youths, is able to explain the recent juvenile crime spike in Uruguay.

A possible extension of this model would be the introduction of government behavior. The government would decide the total expenditure in the fight against crime and how to allocate these resources. A standard approximation would be to minimize the present discounted value of the crime burden by choosing both the investment in street surveillance and the resources spent to manage detention centers, subject to an intertemporal budget constraint. However, I decided to exclude government behavior from the analysis for two reasons. First, this is a model analyzing the behavior of minors, who represent only 8 percent of the total population. Thus, in order to introduce the government, I would also have to introduce taxes paid by adults to finance government expenditure, and the behavior of adults is out of the scope of this model. Second and more importantly, given that the magnitude of the elasticity of police crime surveillance remains undefined in the literature (Levitt 2002), government behavior would be impossible to calibrate with precision. The exclusion of the public sector prevents the introduction of government welfare transfer payments into the model, which could affect the decision between working or committing crime. In fact, while unconditional transfer payments would have no effect on the model's decisions, conditional ones (on legal activities) could affect the individual's choice to engage in either legal or criminal activities.

Model results suggest that an increase in the expected punishments of young offenders in the juvenile justice system is a better way to fight juvenile crime than an early transition to adult crime courts. The first alternative not only predicts a similar reduction in juvenile offending but also avoids negative consequences in terms of adult criminal involvement.

This result is consistent with the literature that suggests a U-shaped relationship between severity of punishment and future criminal behavior, with an optimal level of punishment minimizing the likelihood of recidivism (Pinchler and Romer 2011). Harsher punishments would reduce recidivism if the levels of punishments are relatively low, and harshness would increase recidivism if punishments are relatively high. Thus, the optimal level of punishment should deter offenders and minimize re-offense by facilitating future

reintroduction into the legal economy. The model calibrated for Uruguay suggests that the increase in the expected punishment within the juvenile system seems to be on the downward side of this "U" whereas the reduction of the age of majority in the upward side.

The introduction of harsher punishments should seek to avoid the school-of-crime effects of juvenile confinement. Empirical evidence suggests that the social environment of juvenile correctional centers is criminogenic due to peer influence (Bayer at al. 2009; DeLisi et al. 2011). Alternative measures such as the introduction of electronic monitoring bracelets for juveniles should thus be considered. Under this system, which might reduce recidivism by up to 40 percent according to Di Tella and Schargrodsky (2010), correctional facilities employees verify whether the juveniles are violating a set of pre-established conditions, such as attending school and work. However, much work remains to be done to deeply understand the rehabilitation process of youth offenders.

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FRUSTRATION, EUPHORIA, AND VIOLENT CRIME

Abstract

We exploit a series of natural experiments to investigate the effect of a violation of expectancies on violent crime. We study two types of violation of expectancies that generate the emotions of frustration and euphoria. Our empirical designs exploit differential expectations (as measured by the odds of soccer games in the betting market) while maintaining the outcome unchanged (a loss in a soccer game for frustration, a win in a soccer game for euphoria). We find that frustration is followed by a spike in violent crime whereas euphoria is followed by a reduction in violent crime. The two effects are concentrated in a narrow time window after the end of the game: one hour.

I. INTRODUCTION

When subjects are exposed to a violation of expectancies they experience an emotional reaction. If reality is worse than expected the resulting emotion is called frustration and if reality is better than expected the resulting emotion is called euphoria or elation (Amsel 1992; Flaherty 1996). Here, we exploit a series of natural experiments in order to study the link between frustration, euphoria, and violent crime.

The ideal experiment on the effects of frustration and euphoria involves a manipulation of expectations while maintaining the outcome unchanged, an approach that, so far, has been restricted to lab experiments in animals. A typical lab experiment involves two phases. First, subjects in the treated group are trained to respond for a reward of a constant value, creating the expectancy of the same reward in the future. Second, the reward is diminished (frustration) or increased (euphoria) without prior notice, so that expectancies are violated. Finally, the effect of frustration or euphoria is addressed by comparing the behavior of subjects in the treated group to those in a control group that receive the same output but that are not exposed to a violation of expectancies. Under the emotional state of frustration animals show significant changes in physiology (Tranel 1983; Otis and Ley 1993; Scheirer et al. 2002; Papini 2003), neural activity (Abler, Walter, and Erk 2005), and behavior (Crespi 1942; Weinstein 1981; Vacca and Phillips 2005). In particular, frustration causes an increase in aggressive behavior for birds (Dantzer, Arnone, and Mormede 1980), pigs (Duncan and Wood-Gus 1971), and rats (Tomie, Carelli, and Wagner 1993), among other vertebrates.

In humans, the potential causal relationship between frustration and aggression (the so called frustration-aggression hypothesis) has been present in the literature of experimental psychology for more than seventy years (Dollard et al. 1939; Berkowitz 1969). However, the empirical support for this hypothesis is meager (Whitley and Kite 2010), probably because it is difficult and ethically problematic to induce experimental

subjects to behave aggressively (Gottfredson and Hirschi 1993; Baumeister et al. 2010). To overcome the difficulties faced by lab researchers, we exploit a series of natural experiments that use real crime data in order to explore the link between frustration, euphoria, and violent property crime. Our setup exploits a unique database that includes the exact time of all crimes reported in Montevideo, Uruguay, between 2002 and 2010. We focus on property crime, which has two categories: theft (property crime without violence) and robbery (property crime with violence). We combine these data on crime with a database that includes the results of all soccer games played by the main Uruguayan teams in that period, and with a database that includes the odds in the betting market. The combination of information from the betting market and the actual result of the game allow us to categorize periods as being of predominant frustration, euphoria, or no-surprise. We find that frustration is followed by a spike in violent crime, thus providing empirical support to the frustration-aggression hypothesis. We also find that euphoria is followed by a reduction in violent crime. The spike in violent crime after frustration and the dampening in violent crime after euphoria are concentrated in a narrow time window after the end of the game: one hour.

There is a vast literature on the impact of incidental emotions (emotions triggered by a prior experience that is irrelevant to the current situation) such as happiness, fear, and anger on decision making (Vohs, Baumeister, and Loewenstein 2007). Incidental emotions influence how much people help (Manucia, Baumann, and Cialdini 1984), trust (Dunn and Schweitzer 2005), and are willing to share in an ultimatum or in a dictator game (Andrade and Ariely 2009). Incidental emotions also influence economic decision making such as risk-taking behavior (Kugler, Connolly, and Ordóñez 2012) and pricing of different products (Lerner, Small, and Loewenstein 2004). We contribute to this literature by providing the first estimates of the effect of the incidental emotions of frustration and euphoria on decision making, in particular on the decision to engage in violent crime.

Close to our approach is the recent paper by Card and Dahl (2011), who explore the relationship between family violence and the emotional cues associated with wins and losses by professional football teams in the US. Under the assumption that outcomes are as random conditional on expectations, they estimate the causal effect of an upset outcome of the game. Their main finding is that upset losses (losses when expected to win) by the home professional football team lead to an increase in police reports of at-home male-on-female intimate partner violence. The estimation of the impact of an upset outcome involves two different things happening together: the impact of the outcome of the game and the impact of a violation of expectancies. Our contribution to this literature is to isolate the impact of the violation of expectancies from the impact of the outcome of the game. We believe this is important, since a violation of expectancies may arise in very different settings and situations that are not necessarily related to sports.

More generally, our findings provide support to Koszegi and Rabin's (2006) prediction that individuals frame gains and losses around a rationally expected reference point (for a review of the literature on the importance of reference points in observed behavior, see Della Vigna 2009). Our paper is also related to the literature on the link between sports and violence (Gantz, Bradley, and Wang 2006; Rees and Schnepel

2009; Priks 2010).

The chapter continues as follows. Section II describes the data and presents the statistical methods. Section III presents the experimental designs and reports the results. Section IV concludes.

II. DATA AND STATISTICAL METHODS

Data on Crime

The database on crime was obtained from the Police Department of Montevideo and includes more than 835,000 felonies occurred in Montevideo from January 2002 to December 2010 (Montevideo, the capital of Uruguay, has a population of 1.5 million of inhabitants, roughly half of the population of the country). It comprises the universe of police-recorded offenses, with information on the date and the exact hour of the incident.

A critical feature of the database is that includes real-time information. The time of the offense is recorded as soon as the crime is reported. Under the usual procedure, the police officer takes detailed information from the victim that includes the time of the incident. Given the precision required for our research, this is a key advantage relative to other sources of crime information such as victimization surveys. Although victimization surveys avoid the usual under-reporting problem of police-recorded offenses, the exact time of the occurrence is generally missed since the victim is asked to recall the details of an event that occurs several months ago.

We focus on property crime, which encompass the two most frequent types of crime: theft and robbery. Theft is defined as depriving a person of property without the use of violence (60 percent of all police-recorded offenses in Montevideo in the period 2002 to 2010), whereas robbery is defined as depriving a person of property with the use of violence or threat of violence (10 percent of the offenses in our database). Violence is defined as an intentional use of physical force or power.

Summary statistics are reported in Table 1.

Table 1. Summary Statistics.

	Frequency	Unit	Mean	St. Dev.	Min.	Max.	Obs.
Robberies	hourly	offenses	1.0	1.2	0	10	78,312
Thefts	hourly	offenses	6.3	3.5	0	33	78,312
Temperature (average)	daily	Celsius	16.3	5.3	3.0	30.9	3,270
Rainfall	daily	mm	3.2	10.1	0	138	3,287
Holidays	daily		0.04	0.20	0	1	3,287
Sunshine	daily	hours	7.2	4.1	0	14.1	3,287

Data on Soccer Results and Odds in the Betting Market

Aside from crime data, our database includes information on the date, the exact hour, and the results of every official game played either by Nacional or Peñarol (the two Uruguayan biggest soccer teams) between 2002 and 2010. Our focus on soccer games is motivated by the fact that in Uruguay most of the population feels strong emotional attachment to one of these two teams.[21] According to a recent poll, in Montevideo 80 percent of the population supports either Peñarol or Nacional (approximately 40 percent for each team), around ten percent support one of the multiple small teams, and the remaining ten percent have no preference for any soccer team.[22]

Finally, the database incorporates the information on the complete record of odds in the betting market for all the games played by Nacional and Peñarol since 2005. We use the odds in the betting market as a proxy for fans' expectations. The bets provide relatively accurate predictions of the final result of the matches: the correlation between being the favorite team according to the bets and winning the game is 0.40 (significantly different from zero at the 1 percent level).

Statistical methods

To explore the effect of frustration and euphoria on property crime we track the number of thefts and robberies in Montevideo in the 7-hour window centered on the end of games played by Nacional and Peñarol. For a given soccer match, we define hour zero as the hour in which the end of the game effectively occurs (thus hour cero is not always the same chronological hour). Hour one is then defined as the hour immediately following the end of the game, hour minus one is the hour preceding the end of the game, and so on. This event-study methodology is well known in empirical finance (Fama et al. 1969; Browman 1983; MacKinlay 1997).

We define crime to be unusually high (low) when the number of crimes recorded is significantly higher (lower) than the number of crimes observed the same day at the same hour in the previous week. For instance, we say that crime is unusually high when the number of crimes on Sunday 16 November 2008 at 5pm is significantly higher in statistical terms than the number of crimes on Sunday 9 November 2008 at 5pm.[23] By computing week variations, we control for the daily and weekly cycles observed in crime (one week is a relatively short period of time in order to have variations in crime trend levels). In addition, we compute the change in crime with respect to a control group (as defined below). That is, to detect abnormal crime we compute a double difference: difference with respect to the previous week plus difference with

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[21] "All the Uruguayans are born shouting a goal and that is why there is so much noise in the maternity wards, there is a tremendous din. I wish to be a soccer player as all Uruguayan children do" (Galeano 1995).

[22] MPC: "Peñarol y Nacional son dos de las tres instituciones en el mundo con mayor número de hinchas en relación a la población de su país."

[23] Assuming that the weekly variations in police-recorded offenses are independently and identically distributed, we cannot reject the null hypothesis that week variations in police-recorded offenses follow a normal distribution.

respect to a control group.

III. EXPERIMENTAL DESIGNS AND RESULTS

The first experiment identifies the causal effect of frustration on crime by comparing the number of crimes after an unexpected loss (the treated group) to the number of crimes after an expected loss (the control group). By exploiting differential expectations while maintaining the outcome unchanged, this design allows us to distinguish frustration from other related emotions arising from just losing a game.

The second experiment identifies the causal effect of euphoria on crime by comparing the number of crimes after an unexpected win (the treated group) to the number of crimes after an expected win (the control group). Again, this design allows us to distinguish euphoria from other related emotions arising from winning a game. The experimental designs are described in Table 2.

Table 2. Experimental Designs.

Experiment	Parameter Estimated	Group	Outcome	Expectation	Sample Size
I	Frustration	Treated	Lose	Win	67
	E(W)-E(L)]/L	Control	Lose	Lose	19
II	Euphoria	Treated	Win	Lose	18
	E(L)-E(W)]/W	Control	Win	Win	205

The identification assumption is that expectations are as random conditional on outcomes. Identification would be challenged in the presence of omitted variables that are correlated with both expectancies and crime. For example, if more fans attend a game in which their team is favored to win and the number of fans attending a game is correlated with crime, this would create a bias in our estimates.

To address the potential concern of omitted variable bias our strategy is as follows: under the assumption that omitted variables should affect violent and non-violent crime in a similar way, the presence of an effect of a violation of expectations on violent crime in combination with the absence of an effect of a violation of expectancies on non-violent crime can be interpreted as providing support to our identification assumption.

We provide evidence to support the assumption that omitted variables affect in a similar way the two types of property crime. First, thefts and robberies have a similar daily and weekly pattern (Figure 1). During the day, thefts and robberies present low levels of criminal activity early in the morning, a steady increase since 5-7am leading to a peak at 8pm. Throughout the week, thefts and robberies look relatively flat from Monday to Thursday, present a peak on Friday, and a decrease during the weekend. Second, thefts and robberies react in a similar way to the set of observable covariates. As shown in Table 3, thefts and robberies

have a positive trend during the sample period. In addition, thefts and robberies rise with temperature and hours of sunshine, and decrease with temperature squared, rainfall, and during holidays.

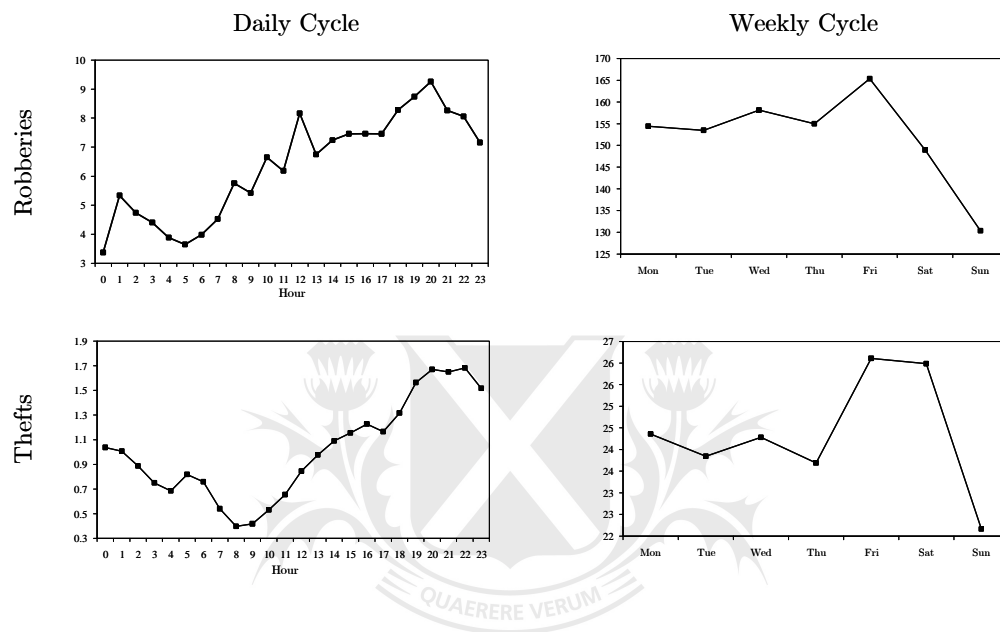Figure 1. Daily and Weekly Cycle of Robberies and Thefts (average 2002-2010).

Table 3. Determinants of Robberies and Thefts.

	Robberies (1)	Thefts (2)	Robberies (3)	Thefts (4)
Temperature	0.341**	4.382***	0.299**	3.002***
	(0.139)	(0.624)	(0.130)	(0.472)
(Temperature^2)	-0.009**	-0.127****	-0.009**	-0.088***
	(0.004)	(0.020)	(0.004)	(0.016)
Rainfall	-0.033***	-0.091*	-0.039***	-0.022
	(0.012)	(0.052)	(0.011)	(0.033)
Holidays	-5.602***	-30.015***	-5.147***	-32.037***
	(0.696)	(3.687)	(0.685)	(3.266)
Daylight	0.028	0.744***	0.031	0.551***
	(0.031)	(0.144)	(0.029)	(0.105)
Linear trend	0.004***	0.011***		
	(0.000)	(0.001)		
Day of the week dummies	Yes	Yes	Yes	Yes
Month dummies	Yes	Yes	Yes	Yes
Year dummies	No	No	Yes	Yes
Observations	3,270	3,270	3,270	3,270

Notes: All models are estimated by OLS. Newey-West robust standard errors are in parentheses.
***Significant at 1 percent level; **Significant at 5 percent level; *Significant at 10 percent level.

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Overall, our assumption that thefts and robberies react in a similar way to unobservable characteristics is supported by the fact that robberies and thefts (i) have a similar daily pattern, (ii) have a similar weekly pattern, (iii) have a positive trend during the sample period, and (iv) react in a similar way to observable characteristics.

Frustration

We identify the impact of frustration on crime by comparing the number of crimes after an unexpected loss (E(W)/L) to the number of crimes after an expected loss (E(L)/L). Thus, we want to estimate [E(W)-E(L)]/L, where L denotes a loss, W a win, and E(.) the pre-game expectation.

This experiment is based on the games that Nacional and Peñarol lost against other teams. In our sample period there are 67 games where the odds anticipated the big teams to be winners but they finally lost (the treated group), and 19 cases where the big teams were expected to be defeated and they lost the game (the control group). We present the results for the treated group, the control group and the difference of both groups in Table 4.

Table 4. Treated Group, Control Group and Frustration.

Hour	Treated Group E(W)/L		Control Group E(L)/L		Frustration [E(W) - E(L)]/L	
	Robberies (1)	Thefts (2)	Robberies (3)	Thefts (4)	Robberies (5)	Thefts (6)
-3	-0.030	0.364	0.211	0.105	-0.241	0.258
	(0.184)	(0.518)	(0.443)	(0.901)	(0.480)	(1.039)
-2	-0.121	-0.030	-0.632	2.053	0.510	-2.083
	(0.184)	(0.489)	(0.406)	(1.171)	(0.446)	(1.269)
-1	0.060	0.701	0.737	-0.105	-0.677	0.807
	(0.203)	(0.414)	(0.365)	(0.625)	(0.418)	(0.750)
0	-0.134	0.075	-0.368	0.211	0.234	-0.136
	(0.171)	(0.461)	(0.427)	(1.091)	(0.460)	(1.185)
1	0.343**	-0.030	-0.684	1.579	1.027***	-1.609
	(0.172)	(0.587)	(0.342)	(1.035)	(0.383)	(1.190)
2	0.045	0.179	-0.158	0.263	0.203	-0.084
	(0.233)	(0.555)	(0.279)	(0.783)	(0.363)	(0.960)
3	-0.567***	-0.687	-0.368	-0.947	-0.199	0.261
	(0.240)	(0.521)	(0.384)	(0.763)	(0.453)	(0.923)

Notes: Standard errors are in parentheses. ***Significant at 1 percent level; **Significant at 5 percent level.

As shown in column (5) in Table 4, violent crime (as measured by robberies) shows a significant jump after a frustrating loss.[24] The increase in violent crime after frustration is quantitatively important: the number of robberies increase 70 percent with respect to the control group. The effect of frustration on violent crime is short-termed, being statistically significant only for the first hour from the game end. This finding is in line with the emotion literature, which has traditionally worked under the assumption that the intensity of an emotional state fades away rather quickly, along with its impact on behavior (Isen, Clark, and Schwartz 1976; Ekman 1999).

As reported in column (6) in Table 4, there is no statistically significant variation in thefts after a frustrating lost. Indeed, the number of thefts is decreasing one hour after the end game, suggesting a possible substitution between violent property crime and non-violent property crime.

The finding that violent crime is increasing and non-violent crime is decreasing (or at least not increasing) provides empirical support to our identification assumption.[25] Our empirical strategy, for example, controls for possible confounding factors such as temperature and rainfall that affect both thefts and robberies. The only identification concern should arise from those confounding factors that are correlated with violent crime but not with crime per se. For example, identification would be jeopardized if games where the big team is expected to win attract a more violent attendance to the stadium, and this more violent attendance is in turn associated with more robberies but not with more thefts. To address this concern we exclude from the sample those crimes committed in the jurisdiction of the stadium where the game was played (Montevideo has 24 jurisdictions), and we find similar results. This indicates that the increase in violent crime is not explained exclusively by unruly behavior of fans attending the game. Instead, the spike in violence spreads over the entire city. We also collected data on the amount of money spent in gambling for the games included in our sample (a proxy for how much expectation generates the game). We find that the amount of money spent in gambling is not correlated with the pre-game bets. This indicates that even if this variable belongs to the model of violent crime, its omission is not biasing our estimates.[26]

Euphoria

The second experiment identifies the effect of euphoria on crime by comparing the number of crimes after an unexpected win to the number of crimes after an expected win ($[E(L)-E(W)]/W$). In our sample period there are 18 games where the odds anticipated the big teams to lose but they finally won ($E(L)/W$, the treated group), and 205 cases in where the big teams were expected to win and ended up winning the game

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[24]Columns (1) and (3) in Table 4 show that the results are driven by the treated group and not by the control group.

[25]The non-significant finding on thefts also suggest that the results are not driven by an over reporting of crime due to emotional cues.

[26]In line with our findings and interpretation, Card and Dahl (2011) report a low correlation between the fraction of households watching a game and the pre-game spread, and interpret the result as evidence that their results are not driven by changes in viewership.

(E(W)/W,the control group).[27] We present the results for the treated group, the control group and the difference of both groups in Table 5.

Table 5. Treated Group, Control Group and Euphoria.

	Treated Group E(L)/W		Control Group E(W)/W		Euphoria [E(L)-E(W)]/W	
Hour	Robberies (1)	Thefts (2)	Robberies (3)	Thefts (4)	Robberies (5)	Thefts (6)
-3	0.278 (0.411)	0.000 (0.836)	0.000 (0.106)	0.068 (0.284)	0.278 (0.424)	-0.068 (0.883)
-2	0.444 (0.372)	-0.778 (0.586)	0.034 (0.108)	0.307 (0.288)	0.410 (0.388)	-1.085 (0.653)
-1	0.000 (0.443)	-1.111 (0.820)	-0.190 (0.108)	-0.107 (0.250)	0.190 (0.456)	-1.004 (0.858)
0	0.222 (0.375)	-1.111 (0.771)	0.180 (0.117)	0.098 (0.272)	0.042 (0.393)	-1.209 (0.817)
1	-1.000** (0.443)	0.444 (0.988)	0.024 (0.109)	0.176 (0.283)	-1.024** (0.456)	0.269 (1.027)
2	-0.444 (0.414)	-0.111 (0.911)	-0.107 (0.130)	0.107 (0.287)	-0.337 (0.434)	-0.218 (0.955)
3	-0.556** (0.232)	-0.333 (0.709)	-0.122 (0.140)	0.293 (0.286)	-0.434 (0.271)	-0.626 (0.765)

Notes: Standard errors are in parentheses. **Significant at 5 percent level.

As observed in column (5) in Table 5, euphoria has the effect of reducing violent crime, a reduction that, again, is only statistically significant for one hour after the game end.[28] The reduction in the number of robberies is 42 percent relative to the control group. Again, there is no impact of euphoria on thefts (column (6) in Table 5).

Finally, our empirical strategy that tracks both violent and non-violent property crime avoids alternative explanations for the observed results such as incapacitation.[29] If celebrations after euphoric victories reduce criminal activity and the lack of celebrations after frustrating defeats increase criminal activity these effects should affect both violent and non-violent crimes. Neither frustration nor euphoria significantly affects the number of thefts.

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[27]In order to increase statistical power we include in the sample international games (that is, games played by Nacional and Peñarol against teams from other countries) played between 2002 and 2005. For these games there is no information available on bets. However, given that in the period 2005-2010 (when odds are available) for international games the home team was the favorite to win in more than 96 percent of the games, we assume that for those international games played between 2002 and 2005 the favorite is always the home team.

[28]Columns (1) and (3) in Table 5 show that the results are driven by the treated group and not by the control group.

[29]The incapacitation effect is well accepted by economists and criminologists to be an important predictor of criminal activity.
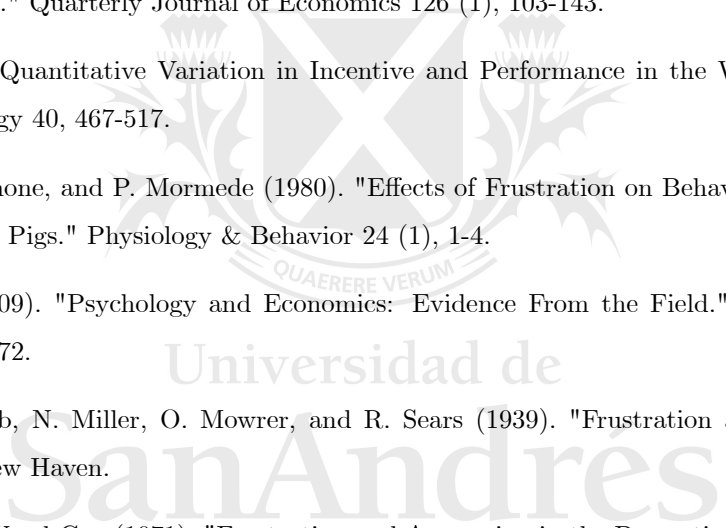
IV. CONCLUSIONS AND DISCUSSION

Our results show that emotional cues have a socially meaningful effect on behavior. In particular, emotions associated to an unexpected soccer result produce a significant variation in fans' aggressive behavior, increasing violent crime after frustration and reducing violent crime after euphoria. The fact that a violation of expectancies has a significant effect on violent property crime but no effect on non-violent property crime lead us to believe that the link between the violation of expectancies and the increase in violent property crime is causal.

Our findings, in combination with the previous findings in animals, indicate that the link between frustration and aggression is a general phenomenon in nature, and suggest an underlying physiological mechanism shaped by natural selection. There is an important body of research showing that under the emotional state of frustration the body releases catecholamine hormones, including adrenaline and noradrenaline. These hormones provide the body a burst of energy and facilitate immediate physical reactions associated with a preparation for violent muscular action (the fight-or-flight response, first described by Canon 1915), reducing in this way the entry cost into violence. Indeed, it is well documented that the release of catecholamine is positively correlated with aggressive behavior (Ekkers 1975; Hamburg, Hamburg, and Barchas 1975; Bell and Hepper 1987).

The literature on rational choice theory in criminology postulates that rational agents decide whether to engage in criminal activities by comparing the benefits and costs of committing a crime, i.e. agents compare the financial reward from crime to the return from legal work, taking into account the probability of apprehension and the severity of the punishment (Becker 1968). Our results indicate that the decision to engage in violent property crime is also influenced by the emotional state of the offender, and suggest that a fraction of crime against the property can be better characterized as a breakdown of control rather than a behavior driven by rational choice.

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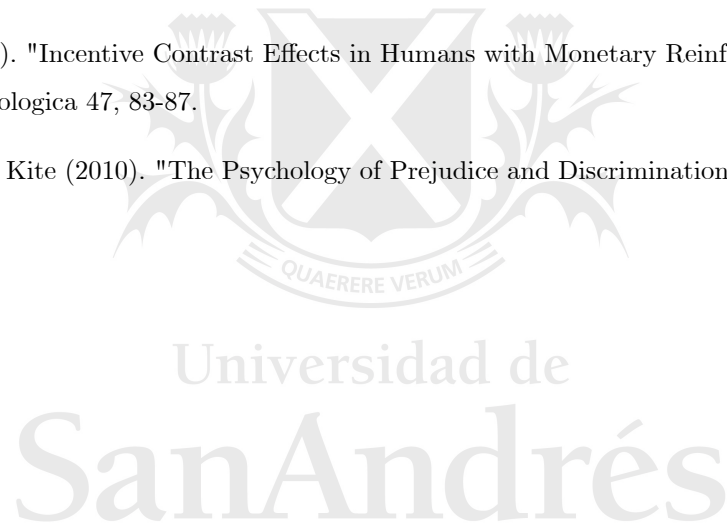
FIRST-DAY RECIDIVISM

Abstract

We find that on any given day the number of inmates released from incarceration significantly affects the number of offenses committed that day. Our estimates are robust to a variety of alternative specifications. We run a series of placebo experiments that further support our causal interpretation of the results. We also find evidence that an increase in the amount of money received by prisoners at the time of their release significantly decreases first-day recidivism, and that first-day recidivism is restricted to crimes with a direct financial motivation. These findings suggest that our results are driven by liquidity constraints.

I. INTRODUCTION

Criminal recidivism of former prisoners is a widespread phenomenon. Recidivism rates are 65 percent in the US (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 (Inter-American Commission on Human Rights 2011), just to mention a few examples.

In this chapter, we focus on re-offenses 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 that day, and we interpret this as evidence of first-day recidivism. Our results are robust to the inclusion of day of the week, year, and year/month fixed effects, and also to controlling for holidays, rainfall, sunshine, and temperature. The magnitude of first-day recidivism is not only statistically significant but also quantitatively substantial: assuming that released prisoners will commit at most one crime a day, approximately 25 percent of released prisoners reoffend on their first day of freedom. To the best of our knowledge, this paper provides the first estimates in the literature on the magnitude of the re-offence rate during the very day prisoners are released.

To explore the reasons underlying first-day recidivism we follow a two-fold strategy. First, we take advantage of the variability produced by a significant increase in the gratuity given to inmates the day of their release. We find that an increase in the gratuity at release produces a significant decrease in first-day recidivism. Second, we show 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. These findings are consistent with temporal displacement in crime (e.g., the shifting of criminal activity from one time to another) driven by an income effect in a context of liquidity constraints.

We contribute to an important body of 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).[30] Evidence indicates most criminal recidivism occurs within the first year after release (Langan and Levon 2002). For example in the United States, 30 percent of offenders are rearrested within the first six months of their release and 44 percent within the first year. Similar figures apply in Australia (Jones et al. 2006). Here, we focus on the estimation of re-offenses instead of following the usual procedure of using records on re-arrest or re-conviction. In this way, our approach allows the inclusion of a large pool of offenses usually omitted in standard statistics.[31]

Our findings are related to the literature on the causal effect of incarceration rates on crime. While estimate magnitudes are sensitive to estimation methodology, most careful research finds that an increase in incarceration rates leads to a reduction in crime (see Marvell and Moody 1994; Levitt 1996; Owens 2009; Johnson and Raphael 2010). Our paper complements this finding by showing that an increase in releases leads to an increase in crime. In the prior work most closely related to our own, Kovandzic et al. (2004) study the link between prison releases and homicides using yearly data for 46 US states from 1975 to 1999 and find no significant evidence of a positive relationship. The lack of significant effects of releases on homicides is consistent with our finding that the driver of first-day recidivism is a liquidity constraint. Indeed, we find that first-day recidivism only affects property crime.

Our result on the effects of an increase in the payment received by prisoners at release is related the literature 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. 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 chapter continues as follows. Section II describes the data and presents the statistical methods. Section III reports the results. Section IV concludes.

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

[31] 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.

II. DATA AND STATISTICAL METHODS

Our dataset includes more than 690,000 felonies which occurred in Montevideo between January 1st 2004 and March 15th 2011 (2,631 days).[32] It comprises the universe of criminal incidents recorded at the Police Department of Montevideo, with information on the date and the geographical identification of the incident.

The two most frequent types of crime in Montevideo 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 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. Summary statistics are reported in Table 1.

Table 1. Summary Statistics.

	Mean	St. Dev.	Minimum	Maximum	Observations
Total crime	270.185	32.655	2	400	2,631
Property crime	191.703	27.634	1	321	2,631
Non-property crime	78.482	13.743	1	161	2,631
Releases	5.927	6.486	0	59	2,631
Temperature (centigrade)	16.551	5.408	3	29	2,631
Rainfall (millimeters)	2.898	9.680	0	125	2,631
Sunshine (hours)	7.269	4.052	0	14	2,631
Holliday	0.043	0.191	0	1	2,631

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).

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). Approximately 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 (Junta Nacional de Drogas 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

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

Prisoners threshold of 120 inmates per 100 slots available. Living conditions for the inmates are inadequate (Inter-American Commission on Human Rights 2011).[33] In addition, rehabilitation and social reinsertion activities are practically absent as opportunity to engage in productive activities when convicted are very scarce (United Nations 2007).

On average six inmates are released every day. In our sample period, about half of the inmates were released after a theft conviction and ten percent after a robbery one. 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).

Under the usual procedure, inmates are informed of their pending release as close as one day prior to actual release. 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. When released, ex-inmates cannot take anything with them (other than the clothes they wear). Until September 5th 2010, at the time of release inmates were given a gratuity of UR$30 (1.5 US Dollars), an amount which barely covered returning to their homes on public transportation. On September 6th 2010, this amount was increased to UR$100.

Statistical Methods

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

$$\text{Offenses}_{tmy} = \alpha + \beta\text{Releases}_{tmy} + \varphi\text{X}_{tmy} + \varepsilon_{tmy} \qquad (1)$$

where Offenses_{tmy} is the total number of offenses on day t, month m, and year y, Releases_{tmy} is the total number of inmates released on day t, month m, and year y, β is the parameter of interest, and ε_{tmy} is the error term. The set of controls, X_{tmy}, 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). 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).

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[33] The harsh conditions at ComCar may explain the relatively high rates of criminal recidivism in Uruguay (see Chen and Shapiro 2007).

III. RESULTS

Given all the series are stationary according to standard unit root tests (see Figure 1), we estimate equation (1) using Ordinary Least Squares (OLS).[34] To deal with potential heteroskedasticity and serial correlation, we compute Newey-West robust standard errors. Following Newey and West (1987), we compute the lag truncation value as $floor[4*(T/100)(2/9)]$ where T is the sample size. Given we have 2,631 observations in our sample we set the lag truncation value at 8.

Figure 1.Total Number of Offenses and Inmates Released.

Notes: Property crime is the sum of thefts and robberies.
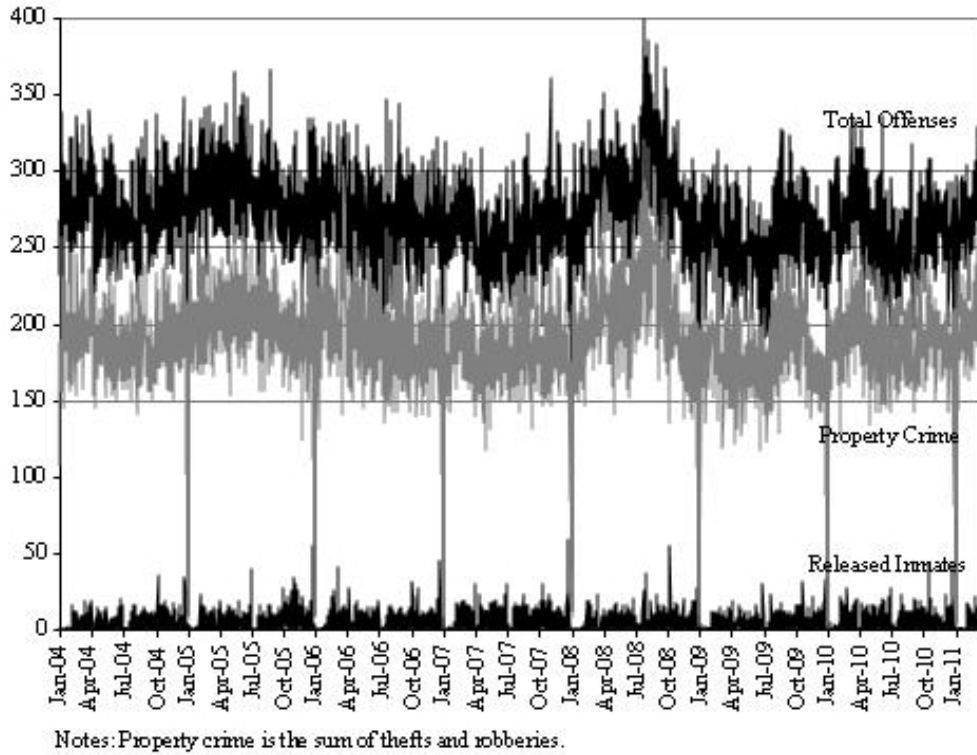
In column (1) of Table 2 we report estimates of equation (1) including a linear yearly trend. The coefficient on the total number of inmates released is positive and statistically significant. Assuming each inmate released commits at most one crime per day, the value of the coefficient indicates that about one out of four inmates commit an offense the very day they are released.[35]

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[34] All results mentioned but not shown are available from the authors upon request.

[35] After running a series of interviews with police officers, we confirm that in the bus that stops at ComCar it is usual to hear conversations between released inmates planning ahead the details of the next imminent crime.

Table 2. Main Results.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Total Crime					
Releases	0.225*	0.216*	0.260**	0.259**	0.198*	0.234**
	(0.124)	(0.123)	(0.123)	(0.123)	(0.115)	(0.096)
Trend	-2.699***	-1.116	-0.008***	-0.236***		
	(0.390)	(1.952)	(0.001)	(0.032)		
Temperature	0.720***	0.733	0.682***	0.682***	0.619***	1.438***
	(0.170)	(0.168)	(0.168)	(0.168)	(0.146)	(0.159)
Rainfall	-0.344***	-0.345***	-0.348***	-0.348***	-0.297***	-0.290***
	(0.054)	(0.054)	(0.054)	(0.054)	(0.051)	(0.049)
Holiday	-25.88***	-25.95***	-25.97***	-25.96***	-25.90***	-25.76***
	(2.763)	(2.768)	(2.757)	(2.756)	(2.637)	(2.341)
Sunshine	0.526***	0.532***	0.540***	0.540***	0.503***	0.961***
	(0.157)	(0.157)	(0.156)	(0.156)	(0.144)	(0.125)
December 31st	-275.0***	-275.2***	-273.1***	-273.3***	-274.0***	-263.4***
	(3.950)	(3.805)	(3.946)	(3.946)	(5.094)	(4.955)
Squared trend		-0.191***				
		(0.226)				
Day of the week dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	No	No	No	No	Yes	No
Year/month combination dummies	No	No	No	No	No	Yes
Observations	2,631	2,631	2,631	2,631	2,631	2,631

Notes: Newey-West heteroskedasticity- and autocorrelation- consistent standard errors are in parentheses. All models are estimated by OLS. A yearly trend is included in models (1) and (2) a daily trend in model (3), and a monthly trend in model (4). *Significant at 10 percent level. **Significant at 5 percent level. ***Significant at 1 percent level.

In the remaining columns in Table 2 we show the results are robust to alternative specifications. Results remain unchanged when we either include a squared yearly trend (column (2)), a daily or a monthly trend instead of a yearly one (columns (3 and 4)), year dummies instead of the yearly trend (column (5)), or when we saturate the model with dummies for month and year combinations (our preferred specification, column (6)).[36]
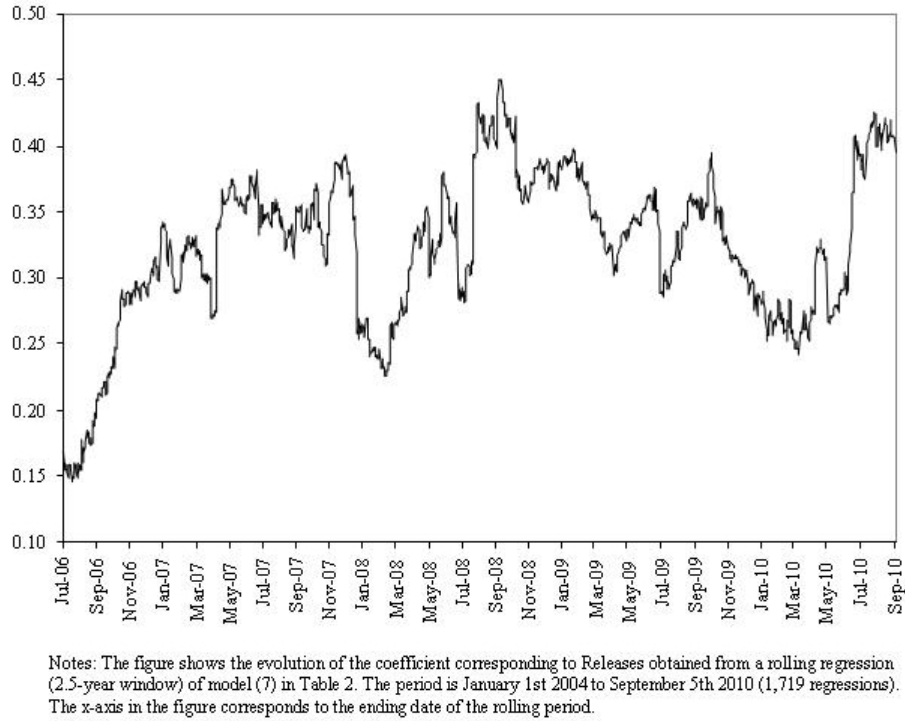
The coefficients of the control variables are as expected: total crime increases with temperature, and decreases with rainfall and on holidays. Hours of sunshine are positively correlated with crime. The coefficients of the day of the week dummies (not reported) show similar crime levels from Monday to Thursday and on Saturdays, a crime peak on Fridays, and an important decrease on Sundays. The coefficients of the month dummies (not reported) show December and January are the months with the least crime.

The incidence of first-day recidivism is not constant over time. In Figure 2 we show the evolution of the coefficient corresponding to Releases for the period January 1st 2004 to September 5th 2010 (the day when the gratuity at release was increased). The coefficients are obtained from a rolling regression (2.5-year window) of our preferred specification (model (6) in Table 2). First-day recidivism presents a positive trend,

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[36] Results remain unchanged if we include an intra-month daily trend.

increasing from 0.15 offenses per released inmates at the beginning of our sample period to 0.42 offenses per released inmates in the period prior to the increase in the gratuity.

Figure 2. Evolution of First-Day Recidivism.

Notes: The figure shows the evolution of the coefficient corresponding to Releases obtained from a rolling regression (2.5-year window) of model (7) in Table 2. The period is January 1st 2004 to September 5th 2010 (1,719 regressions). The x-axis in the figure corresponds to the ending date of the rolling period.

In Table 3 we analyze whether the number of releases in a given day affects crime in the following days. We explore 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 (see columns (1) and (2) in Table 3). These results suggest the correlation between crime and the number of inmates released is significant only in the same day of the release. We also include total crime as a lagged dependent variable. The coefficient associated to Total Crime in t-1 is significant but small (0.063).[37] In all cases, the coefficient on Releases remains unchanged.

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[37] The value of the coefficient implies that the long run first-day recidivism is slightly higher than the coefficient on Releases as this coefficient should be multiplied by a factor of [1/(1-0.063)]=1.067.

Table 3. Robustness Checks.

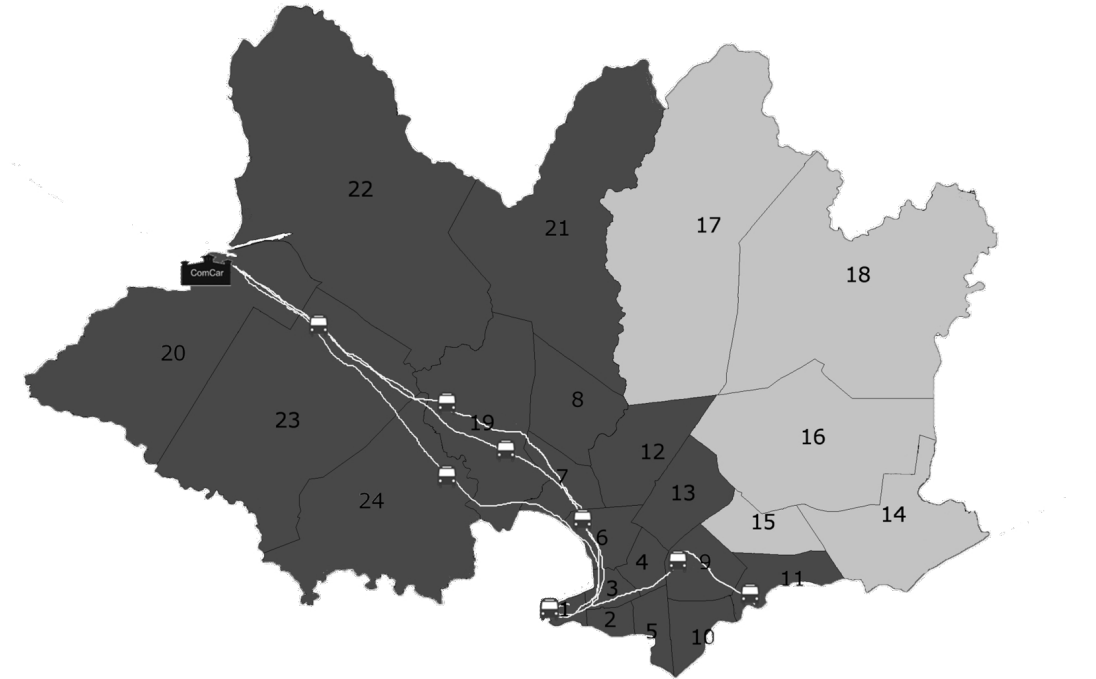|	Dependent Variable: Total Crime		
	(1)	(2)	(3)
Releases	0.244***	0.241***	0.245***
	(0.095)	(0.095)	(0.095)
Releases in t-1	-0.052	-0.053	-0.084
	(0.096)	(0.092)	(0.093)
Releases in t-2		-0.031	-0.023
		(0.087)	(0.087)
Releases in t-3		-0.016	-0.014
		(0.102)	(0.102)
Releases in t-4		-0.004	-0.004
		(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)
Total crime in t-1			0.063***
			(0.020)
Controls	Yes	Yes	Yes
Day of the week dummies	Yes	Yes	Yes
Year/month combination dummies	Yes	Yes	Yes
Observations	2,630	2,624	2,624

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

False Experiments

In order to ensure the results indeed do have a causal interpretation, we run two exercises. In the first exercise, we divide Montevideo in 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).[38] The within-range area encompasses 71 percent of the population, 66 percent of the area, and hosts 74 percent of the crime in Montevideo.

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[38]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.

Figure 3. Within-Range and Out-of-Range Areas.

If the relationship between releases and crime is indeed causal we would expect to find an effect in the within-range area but not in the out-of-range area. This is exactly the case: as shown in columns (1) and (2) of Table 4, while the number of released inmates significantly affects total offenses in the within-range area, there is no effect of releases on total offenses in the out-of-range area.

Table 4. False Experiments.

	Dependent Variable: Total Crime		Dependent Variable: Total Crime in Previous Day
	Within-Range Area	Out-of-Range Area	
	(1)	(2)	(3)
Releases	0.206**	0.034	0.022
	(0.082)	(0.036)	(0.108)
Controls	Yes	Yes	Yes
Day of the week dummies	Yes	Yes	Yes
Year/month combination dummies	Yes	Yes	Yes
Observations	2,631	2,631	2,631

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

In the second exercise, we correlate the number of releases in a given day with the number of offenses in the previous day. As reported in column (3) of Table 4, we find no significant association between these two variables, as expected. These exercises further corroborate the empirical validity and robustness of our results.

Underlying Reasons

In this section we explore possible underlying reasons to our findings. We particularly focus on the hypothesis that first-day recidivism is driven by liquidity constraints. A first implication of this hypothesis is that relaxing the constraint should reduce the effect of first-day recidivism. To test this implication we take advantage of the variability produced by an important increase in the gratuity given to inmates on their release-day. On September 6th 2010 the gratuity increased from UR$30 to UR$100, thus relaxing the first-day cash constraint faced by released prisoners and allowing us to explore the impact that this policy had on first-day recidivism. The UR$ 70 increase in the gratuity at released is indeed important: according to official statistics, in September 2010 the amount of money needed to purchase a basic daily food basket was UR$ 57.

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. If anything, the effective probability of apprehension decreased from 10.7 percent in 2009 to 10.1 percent in 2010.[39] Additionally, there were no legal modifications affecting the level of punishment in the second semester of 2010.

An anticipation of the result 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 our preferred specification (column (6) in Table 2). We consider two periods: January 1st 2010 to September 5th 2010 (66 regressions) and September 6th 2010 to March 15th 2011 (9 regressions). Figure 4 shows clearly that the coefficient on Releases is significantly higher in the period before the increased in the gratuity, presenting a sharp discontinuity on September 5th 2010.

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[39]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 60 percent.

Figure 4. Impact of an Increase in the Gratuity.
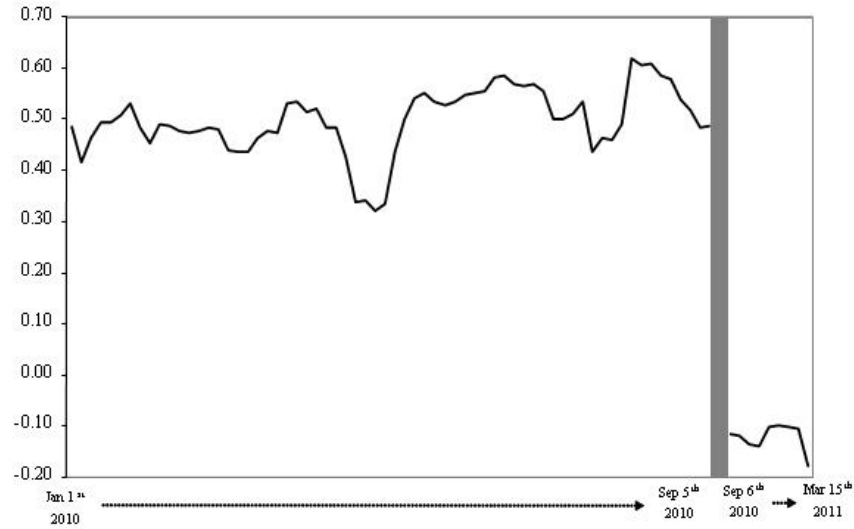
Notes: The figure shows the evolution of the coefficient corresponding to Releases obtained from a rolling regression (six-month window) of model (6) in Table 2. We consider two periods: January 1st 2010 to September 5th 2010 (66 regressions) and September 6th 2010 to March 15th 2011 (9 regressions).

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 a 360-day window around September 5th 2010. As shown in columns (1) and (2) of Table 5, 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 (the p-value for the difference in the coefficients is 0.057). 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. Thus, first-day recidivism is dependant on the gratuity at release.

Table 5. Impact of an Increase in the Gratuity.

	Dependent Variable: Total Crime	
	Before 5th September	After 5th September
	(1)	(2)
Releases	0.587*	-0.120
	(0.303)	(0.237)
Difference of coefficients	(1) − (2) = 0.707	
[p-value for test of Ho: (1)(2) = 0]	[0.057]	
Controls	Yes	Yes
Day of the week dummies	Yes	Yes
Year/month combination dummies	Yes	Yes
Observations	180	180

Notes: Newey-West heteroskedasticity- and autocorrelation- consistent standard errors are in parentheses. All models are estimated by OLS. Controls include rainfall, temperature, a dummy for holidays, hours of sunshine, and a dummy for the 31st of December. The models use data for the 360-day window around September 5th 2010. *Significant at 10 percent level.

A second implication of the liquidity-constraint hypothesis is that first-day recidivism only affects property crime. As shown in column (1) and (2) of Table 6, it does: the effect of releases comes exclusively from property crime. In the other columns of Table 6 we report results by type of crime in both the within-range area and the out-of-range area. Again, we find an impact of releases on property crime that is only statistically significant in the within-range area. There is no impact of releases on non-property crime in both the within-range area and the out-of-range area.

Table 6. Types of Crime.

	Property	Non-Property	Within-range Area		Out-of-range Area	
			Property	Non-Property	Property	Non-Property
	(1)	(2)	(3)	(4)	(5)	(6)
Releases	0.245***	-0.011	0.216***	0.036	-0.010	-0.002
	(0.082)	(0.044)	(0.067)	(0.031)	(0.036)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Day of the week dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year/month combination dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,631	2,631	2,631	2,631	2,631	2,631

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

IV. CONCLUSIONS AND DISCUSSIÓN

This chapter 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 the inclusion of day of the week, year, and year/month fixed effects, and also to controlling for holidays, rainfall, sunshine, and temperature. We also run a series of placebo experiments that provide additional reassurance that the estimates have a causal interpretation. The results are not only statistically significant, they are also quantitatively important: approximately 25 percent of ex-inmates recidivate on the day of their release.

We explore potential underlying reasons to our findings and provide evidence consistent with the hypothesis that the driver of first-day recidivism is a liquidity constraint. First, first-day recidivism is negatively correlated with the amount of money received by prisoners at the time of their release. Second, all first-day recidivism comes from property crime.

Our results are important both for theoretical and policy reasons. From a theoretical perspective, they indicate criminal behavior is consistent with a rational framework in which offenders have liquidity constraints,

as in Jacob, Lefgren, and Moretti (2007). Within this framework, prisoners are prevented from committing property offenses through incarceration: when released, they seek to make-up for lost income by engaging in further criminal activity.

Besides its theoretical implications, our findings also have important policy implications by highlighting the importance of the amount of the gratuity at release as a fundamental aspect of anti-crime policies.

Finally, even though a crime delayed is not necessarily a crime prevented, our paper shows relaxing liquidity constraints does affect criminal behavior opening new avenues for future research.

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