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Theft and Deterrence

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Abstract We report results from economic experiments of decisions that are best described as petty larceny, with high school and college students who can anonymously steal real money from each other. Our design allows exogenous variation in the rewards of crime, and the penalty and probability of detection. We find that the probability of stealing is increasing in the amount of money that can be stolen, and that it is decreasing in the probability of getting caught and in the penalty for getting caught. Furthermore, the impact of the certainty of getting caught is larger when the penalty is bigger, and the impact of the penalty is bigger when the probability of getting caught is larger.

Keywords Experiments · Crime · Larceny · Theft · Deterrence · Penalty · Rationality

Introduction

Becker (1968) created the foundation for the economic analysis of criminal behavior. Since then, economists have extended his basic theoretical framework in several directions, but the basic argument remains – participation in crime is the result of an optimizing individual's response to incentives such as the expected payoffs from

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criminal activity and the costs, notably the probability of apprehension and the severity of punishment.[1] Since the early empirical research that reported evidence that deterrence reduces crime (Ehrlich 1973, 1975; Witte 1980; Layson 1985), the main challenge in empirical analysis has been to tackle the simultaneity between criminal activity and deterrence. Specifically, an increase in deterrence is expected to reduce criminal activity, but a change in crime is also expected to prompt an increase in the certainty and severity of punishment, through mechanisms such as an increase in the arrest rate and/or the size of the police force. This makes it difficult to identify the causal impact of deterrence on crime.[2]

Recent research has employed three types of strategies to overcome the simultaneity problem. The first solution is to find an instrument that is correlated with deterrence measures, but uncorrelated with crime. An example is Levitt (2002) who used the number of per capita municipal firefighters as an instrument for police effort. The second strategy is to use high-frequency time-series data. For example, in monthly data, an increase in the police force in a given month will affect criminal activity in the same month, but an increase in crime cannot alter the size of the police force in that same month because of the much longer lag between a policy decision to increase the working police force and the actual deployment of police officers on the street. This identification strategy has been employed by Corman and Mocan (2000, 2005). The third strategy is to find a natural experiment which generates a truly exogenous variation in deterrence, as in Di Tella and Schargrodsky (2004), who use the increase in police protection around Jewish institutions in Buenos Aires after a terrorist attack to identify the impact of police presence on car thefts, and Drago et al. (2009) who exploit the exogenous nature of a clemency bill passed by the Italian Parliament in 2006 to estimate the impact of recidivism to expected punishment.

Although these empirical strategies have permitted researchers to refine and improve upon earlier estimates, a convincing natural experiment is very difficult to find, the validity of any instrumental variable can always be questioned, and one can argue that if policy makers have foresight about future crime rates, low frequency data could also suffer from simultaneity bias.[3]

In this paper, we use an economic experiment to investigate individual responses to unambiguously exogenous changes in the rewards and penalties of criminal behavior. The experiment involves decisions about actions that can best be described as petty larceny – stealing money from another individual, with a chance of getting caught and having to repay everything taken and a penalty in terms of a monetary fine. The subjects are high school and college students, and the experiment is done using real money payoffs. Our protocol used loaded language, such as "criminal," "victim" and "steal from the victim" to provide explicit reminders of the dishonest and wrong nature of the act. We collect information on (nearly) simultaneous choices

[1] See, for example, Ehrlich 1973; Block and Heineke 1975; Schmidt and Witte 1984; Flinn 1986; Mocan et al. 2005.

[2] See Ehrlich (1996) for a discussion of related theoretical and empirical issues.

[3] Similar difficulties exist in identifying the effect of unemployment and wages on crime. For example, although increases in minimum wages can be argued as being exogenous to crime, the case is less compelling for wages in general, and for the unemployment rate. For various identification strategies see (Hansen and Machin 2002; Gould et al. 2002; Machin and Meghir 2004; Corman and Mocan 2005; Mocan and Unel 2013).

to steal made by individuals facing a variety of different criminal opportunities and tradeoffs between the benefits and costs. In addition to the analysis of how individuals respond to exogenous changes in the costs and benefits of crime, another contribution of the paper is an experimental design that allows us to evaluate the impact of the certainty and the severity of punishment independently and simultaneously. In contrast, empirical studies of crime are generally unable to include measures of *both* the certainty and the severity of punishment, as we explain below.

The experimental economics literature on tax compliance is related to this paper, but there are substantive differences between our experiment and those employed in tax compliance studies (Alm and McKee 2004, 2006; Alm et al. 1992). The design of most tax compliance experiments involves subjects who are given a certain amount of income and who decide on how much of this income to report. Subjects pay taxes on reported income at declared tax rates. Tax evasion is discovered by a random audit and a fine is paid on unpaid taxes. This process is repeated for a number of periods which constitute a session. The impact of a policy change is identified by between-session variation of a parameter such as the audit rate. This is because, by design, all subjects are exposed to one set of parameters that do not change over the course of the experiment (session).[4] In contrast, as explained below, our design identifies the effects of the costs and benefits of committing a crime from within-subject variation. Also, in tax experiments tax evasion by the subjects typically amounts to taking money away from the experimenter. In our design subjects steal money from another participant. The next section provides description of the experimental design. The following section presents the results, and the last section concludes.

Experimental Design

The experiments were conducted with public high school and college students, with IRB approval. Following standard economic experimental protocols we provided complete information to the participants, paid them privately in cash, and there was no deception. Before the experiment, the students read an assent agreement and were allowed to opt out of the experiment, but none did. Because public school attendance rates are high, this procedure provides a fairly representative sample of the area high school age population. However, the sample is not nationally representative – Eugene is a medium sized college town with a population where per capita income and the proportion of whites are higher than the U.S. average.[5]

Each participant was randomly given an endowment of \$8, \$12, or \$16. Their basic decision was how much additional money, if any, to steal from an anonymous partner, given specified probabilities of getting caught and specified fines that must be paid if caught. Our protocol emphasized that the subject's decision would involve what was described as the criminal act of stealing money from a victim. This

[4] One exception is Alm and McKee (2006) where each subject faces one tax rate, one penalty rate, but two audit rates.

[5] As Levitt and List (2007) underscore, self-selection of subjects into an experiment may diminish the generalizability of the results. In our high school experiments there was no self-selection effect, since all the students agreed to participate. Selection in terms of who was recruited was small, since high school attendance is high. Selection on both counts is more significant with our college sample.

language was used to emphasize that this was not a game of chance, and that the decision to steal would involve taking money from a victim in the class, and not from the experimenter. More specifically, the subjects were told that

> "The criminal will have a chance to steal some of the victim's money. However, stealing is not without a risk. If the criminal decides to steal some of the victim's money, there is a chance that the criminal is caught. If the criminal is caught, then he or she will have to return the money taken from the victim, and also pay a fine to the experimenter. The chance that the criminal is caught, and the amount of the fine, depend on the choice made by the criminal."

Everyone made a decision as if they were the criminal, and we then randomly and anonymously paired subjects and randomly determined actual roles (criminal or victim) within each pair, for the purpose of determining the payoffs. The subjects knew the other participants, but they did not know whom they would steal from, or who stole from them, even after the end of the experiment. Anonymity was used in part to eliminate uncontrolled partner specific effects, and in part because of IRB concerns about retaliation.

Subjects made a series of decisions from 13 different choice sets. Each choice set included a list of alternative choices, and subjects were told to pick one alternative from each choice set. Each alternative choice involved different combinations of stolen money, the probability of getting caught, and the fine that had to be paid if caught. Therefore, each alternative can be thought of as a different possible crime. Some potential crimes involved stealing a little amount of money, facing a good chance of getting away with it and a modest fine if caught. Others involved a larger amount of money, but a lesser chance of getting away with it, and so on. Not to steal was always an option. Table 1 displays the menu of bundles for a representative choice set (Choice Set #5 in the experiment). The complete protocol is given in the Appendix.

Table 1 Sample bundles, from choice set # 5

Mark one choice below	Amount to steal from the victim	Chance of being caught	Fine if you are caught
☐	\$0.00	0%	\$0.00
☐	\$2.00	75%	\$0.10
☐	\$2.00	50%	\$2.10
☐	\$2.00	25%	\$4.10
☐	\$4.00	75%	\$1.90
☐	\$4.00	50%	\$3.90
☐	\$6.00	75%	\$3.70
☐	\$8.00	75%	\$5.50

Each subject made one choice from 13 different choice sets, presented in random order. Ten of the choice sets involved alternatives with negative tradeoffs between the characteristics of the stealing choices: choices with more loot meant higher probabilities of getting caught and higher fines. Three choice sets involved choices where increasing the loot was possible while holding the probability and the fine constant, at various levels. Table 2 shows summary information for each of the choice sets, specifically, the minimum and maximums of the possible loot, the probability of getting caught, and the fine that must be paid if caught.

Participants knew their endowment, but not that of their partner. The amount of money that could be stolen ranged from \$0 to \$8. We included this variation to see if an exogenous change in money income changes decisions about stealing. These are relatively high financial stakes. Eight dollars is about half the average weekly discretionary spending of a high school student, and it is 1/10th of the weekly spending for a college student.

After subjects made a choice from each of the 13 choice sets we randomly and anonymously paired them, then randomly determined which of each pair was the criminal and which the victim. One of the criminal's choice sets was randomly chosen, and the choice they made from that particular set was implemented for that pair. If the criminal did choose to steal, we used a randomized procedure to determine whether they got away with it, or were caught and had to return any stolen money to the victim and also pay the fine. The criminal and the victim were then paid the resulting amounts in cash in sealed envelopes.

The experiments were conducted in three high school classes in Eugene, Oregon and two undergraduate classes at the University of Oregon, for a total of 82 high school students and 34 college students. We collected data on standard socio-demographic characteristics of the high school subjects in a post-experiment survey in order to investigate their relationship with participants' choices. Definitions and descriptive statistics of these variables are provided in Table 3. *Oldest Child* is a

Table 2 Choice set characteristics

Choice sets	Loot (min, max)	Probability of getting caught (min, max)	Fine (min, max)
1	\$2.00, \$8.00	25 %, 75 %	\$0.10, \$5.70
2	\$2.00, \$8.00	25 %, 75 %	\$0.10, \$2.90
3	\$2.00, \$8.00	25 %, 75 %	\$0.10, \$5.70
4	\$2.00, \$8.00	25 %, 75 %	\$0.10, \$2.90
5	\$2.00, \$8.00	25 %, 75 %	\$0.10, \$5.50
6	\$2.00, \$8.00	25 %, 75 %	\$0.10, \$2.80
7	\$2.00, \$8.00	25 %, 75 %	\$0.10, \$5.50
8	\$2.00, \$8.00	25 %, 75 %	\$0.10, \$2.80
9	\$2.00, \$6.00	25 %, 75 %	\$0.10, \$4.10
10	\$2.00, \$6.00	25 %, 75 %	\$0.10, \$2.10
11	\$1.00, \$6.00	55 %, 55 %	\$0.60, \$0.60
12	\$1.00, \$6.00	55 %, 55 %	\$1.80, \$1.80
13	\$1.00, \$6.00	5 %, 5 %	\$0.10, \$0.10

In each of the 13 choice sets, there is one option with loot=\$0.00, the probability of getting caught=0 %, and fine=\$0.0. This is the option of not stealing. Thus, the actual minimum values of the loot, the probability of getting caught and the fine are 0.0 in each round. The values in the table pertain to the minimum and maximum values among the choices that involve theft

Table 3 Descriptive statistics of personal characteristics

Variable	Definition	High school	Undergraduate
Age	Age of the individual	16.86 (1.30)	NA
Height	Height of the individual in feet	5.60 (0.36)	NA
GPA[a]	High school grade point average	3.46 (0.50)	NA
Money	How much money the individual spends on his/her own per week	20.72 (28.36)	NA
Male	Dichotomous variable (=1) if the person is male	0.41	NA
One sibling[a]	Dichotomous variable (=1) if the person has one sibling	0.47	NA
Two or more[a] siblings	Dichotomous variable (=1) if the person has two or more siblings	0.46	NA
Oldest child	Dichotomous variable (=1) if the The person is the oldest child in the family	0.48	NA
Years in Eugene	The number of years the person lived in Eugene, Oregon	9.75 (3.61)	NA
N		82	34

[a] GPA information is missing for 3 students; sibling information is missing for 1 student. Socio-demographic data were not collected from the college sample

dichotomous variable to indicate if the subject is the oldest (or only) child in his or her family. *Years in Eugene* stands for the number of years the subject has lived in Oregon - a larger value may be considered as a proxy for enhanced ties to friends and community, and might be expected to have a negative correlation with stealing.

Results

In this section we report the results of the analyses on individuals' decisions regarding whether or not to steal. First, the hypothesis that people will not steal from each other is not supported, on average. Table 4 presents the distribution of the number of thefts. During the experiment each individual had the opportunity to steal 13 times. Thus, zero thefts means that the individual never stole during the experiment, while a 13 indicates that he or she stole something in every choice set. As Table 4 demonstrates, there is substantial variation in the number of thefts. Ten percent of the subjects stole five or fewer times. Forty-seven percent of the subjects stole 13 times during the experiment; that is, they stole some amount of money in very choice set.

We exploited the panel nature of the data and estimated the effects of loot, probability, and fines on the decision to steal, as follows. Let Y_i stand for the indicator variable that takes the value of one if the individual decides to steal, and zero otherwise; and let P stand for the vector that consists of the values of the loot, the probability of getting caught, and the fine, associated with that choice. Assume that subject i has decided to steal in a given choice set – for example, suppose she has decided to choose the last theft in choice set 5, shown in Table 1. She has chosen a

Table 4 Number of thefts

Number of thefts[a]	Number of individuals	Percentage of total
0	5	4.31 %
1	1	0.86 %
2	1	0.86 %
3	1	0.86 %
4	1	0.86 %
5	3	2.59 %
6	2	1.72 %
7	4	3.45 %
8	2	1.72 %
9	8	6.90 %
10	9	7.76 %
11	5	4.31 %
12	19	16.38 %
13	55	47.41 %
Total	116	100 %

[a]The number of thefts is the number of choice sets where the individual stole money. Thus, 0 indicates that the individual did not steal money during the entire experiment, and 13 indicates that he/she stole in every choice set

crime with loot of \$8, a probability of being caught of 75 %, and a fine of \$5.50 if caught. From her observed choice we can make the revealed preference argument that this theft dominates the option not to steal, so Y_i=1 with these values of the loot, the probability of being caught, and the fine that are associated with this crime P=(\$8, 75 %, \$5.50).[6]

A subject, who has decided not to steal from a given choice set, has made a series of decisions not to steal, each relative to the option of stealing. So, again using choice set 5 as an example, the choice with loot=\$2, probability of being caught =75 %, and fine=\$0.10 was not enough for him to make the decision to steal. Thus, in this case, Y_i=0, and P=(\$2, 75 %, \$0.10). The same is true for all other alternatives that involve stealing money in this choice set, and so Y=0 for all other P vectors in choice set 5, given that the person did not steal in that particular choice set.

Table 5 presents the results of the regressions using these data. In these and all other regressions, standard errors are clustered at the individual level. The models behind columns (1)-(3) include individual fixed-effects. An increase in the loot is expected to increase the probability of committing theft. On the other hand, an increase in the probability of getting caught and an increase in the fine should deter the individual from stealing. Column (1) presents the results from the high school sample, and column (2) reports the results based on the sample of college students. In both cases, an increase in the loot increases the propensity to steal and an increase in fine decreases that propensity. The same is true for the probability of getting caught. When we estimated the model by pooling high school and college students, and interacting the explanatory variables with an indicator variable that identifies the

[6] There could be another theft option in the same choice set that could have enticed the subject to steal (see the 7 theft options in Table 1), but given that the subject was allowed to make only one choice from each choice set, we do not observe his second, or third-best theft choices.

high school students, we could not reject the hypothesis that the coefficients were the same between the two groups.[7] Therefore, we estimated the model using the entire sample, which consists of 3,135 observations from 116 subjects. The results, reported in column (3) show that the point estimates of the variables are almost identical to those reported in columns (1) and (2), and that they are highly statistically significant.

The results in columns (1)-(3) of Table 5 indicate that a $1 increase in the amount of money that is available to steal (loot) increases the probability of theft by 3 percentage points. The mean value of the loot in the sample is $3.82, and the baseline theft propensity is 0.36. Thus, the elasticity of theft with respect to money available to steal is 0.32.

Important policy questions hinge on the relative deterrent effects of increased fines versus increased chances of apprehension. Ideally, empirical studies would be done with data that includes independent changes of both variables. However, in practice, empirical analyses do not include measures of both the probability of apprehension and the severity of punishment, because of the paucity of data. While it is possible to measure the probability of apprehension by arrest rates of particular crimes, the severity of punishment is difficult to quantify because data on conviction rates and average sentence lengths are noisy and they are not consistently available. Therefore, crime regressions typically include arrests rates or the size of the police force as measures of the certainty of punishment, with no controls for the severity of punishment.[8 9]

Our design allows us to exogenously vary *both* the certainty and the severity of punishment, and analyze the extent to which these variations induce a change in behavior. We find strong evidence for deterrence effect. Furthermore, our results show that the propensity to steal reacts more strongly to the penalty than to the probability of getting caught. This result is consistent with the theoretical models where the potential offender is risk averse (Ehrlich 1973). With the simplest specification, column (3) in Table 5, we find that a one-percentage point increase in the probability of getting caught decreases the propensity to steal by 0.3 percentage points, which corresponds to an elasticity of −0.4. This elasticity is very similar to the elasticity of felony crimes with respect to their own arrest rates reported by Corman and Mocan (2005) and in Levitt (1998). Similarly, if the fine goes up by $1, we find the propensity to steal declines by about 5 percentage points, which corresponds to a fine elasticity of theft of −0.30.

Column (4) of Table 5 presents the results from the linear probability model that includes personal background characteristics of the individuals instead of individual fixed-effects. Because data on these characteristics are collected only from high

[7] The F-value of the joint significance of the interaction terms was 1.21 with a p-value of 0.31.

[8] One exception is research on the impact of capital punishment, where empirical models include measures of the probability of arrest, the probability of conviction given arrest, and the probability of execution given conviction (Mocan and Gittings 2003, 2010; Ehrlich 1975). Mustard (2003) has personally collected data on conviction rates and sentence lengths from four states and showed that the inability to include these variables because of the lack of data under-states the impact of the arrest rate as much as 50 percent.

[9] Over the last three decades the severity of punishment has been increased in many states in the U.S. with the implementation of sentencing guidelines and mandatory sentencing policies. However, these sentencing reforms are not exogenous events. Furthermore, they generate reactions in the behavior of judges and prosecutors, which make certainty of punishment endogenous to these changes (Bushway et al. 2011; Miceli 2008; Schanzenbach and Tiller 2007).

Table 5 The impact of rewards and sanctions on the propensity to steal

Variable	(1)	(2)	(3)	(4)	(5)
Loot	0.033***	0.040***	0.034***	0.051***	0.046***
	(0.006)	(0.013)	(0.006)	(0.008)	(0.008)
Probability of getting caught	−0.003***	−0.002**	−0.003***	−0.005***	−0.004***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Fine	−0.058***	−0.043***	−0.055***	−0.072***	−0.068***
	(0.010)	(0.015)	(0.008)	(0.011)	(0.011)
Age				0.013	0.012
				(0.031)	(0.029)
Male				0.383***	0.342***
				(0.088)	(0.074)
Height				−0.201	−0.173
				(0.143)	(0.129)
GPA				0.053	0.050
				(0.080)	(0.078)
Endowment				−0.006	−0.005
				(0.010)	(0.009)
Money				0.001	0.001
				(0.002)	(0.002)
Years in Eugene				−0.018*	−0.015*
				(0.009)	(0.009)
One sibling				0.063	0.077
				(0.144)	(0.147)
Two or more siblings				0.294*	0.290**
				(0.149)	(0.146)
Oldest child				−0.007	0.005
				(0.072)	(0.070)
Sample	High school	College	Pooled	High school	High school
Individual FE	Yes	Yes	Yes	No	No
R-square	0.09	0.12	0.10	0.22	0.18#
N	2,509	626	3,135	2,368	2,368

Standard errors, reported in parentheses, are clustered at the individual level. Statistical significance of the coefficients at the 10 %, 5 % and 1 % level are indicated by *, **, and ***. Models in columns (1)-(4) are estimated by OLS. Column (5) reports the average marginal effects obtained from maximum likelihood probit. # represents pseudo-R square

school students, these regressions are restricted to the high school sample. Column (5) displays the marginal effects obtained from a probit regression, and demonstrates that neither the point estimates nor their statistical significance are altered by estimation methodology as the results are very similar to those reported in column (4). The strong deterrence effect is confirmed in these specifications as well. An increase in the probability of getting caught, or in the amount of penalty reduces the incentive to steal as the estimated coefficients are highly significant in columns (4) and (5).

The estimated impacts of personal attributes reveal interesting regularities. Males have a higher propensity to steal than females, which has been well-documented in empirical studies (Mocan and Rees 2005; Gottfredson and Hirschi 1990; Hagan et al. 1979). The longer the individual has lived in the town where the experiments were conducted, the lower his/her propensity to steal. Specifically, an additional year of residence reduces the propensity to steal by about 2 percentage points. This result may be due to the fact that longer residency is correlated with stronger personal networks, which in turn reduces the propensity to steal - despite the fact that the victim is always anonymous. As Levitt and List (2007) describe, utility maximization in situations like this may also involve not only monetary payoffs, but also concerns about "doing the right thing" or "moral choices." In our setting, the declining propensity to steal as a function of the length of residency in the city seems consistent with the hypothesis that difficult-to-observe determinants of behavior such as "morals" may in part be determined by considerations of the environment.[10] The significance of the residency variable suggests that the subjects did not treat the experiment as a game of chance - if they had, the length of residency would not have any impact on their behavior.

Columns (4) and (5) also show that the age, the height and the GPA of the individual have no impact on the propensity to steal.[11] The same is true for the amount of money they spend each week. Similarly, the endowment given to them in the beginning of the experiment ($8, $12 or $16) has no impact on the decision to steal. On the other hand, those who have two or more siblings have a higher propensity to steal in comparison to those who have one sibling or no siblings. This result is in line with a large literature in economics, sociology and demography which demonstrates the negative impact of family size on child outcomes (Blake 1981; Becker and Lewis 1973; Downey 1995; Cáceres-Delpiano 2006).[12]

In our final specifications we added an additional explanatory variable, the interaction term between the probability of getting caught and the fine to the specifications. The hypothesis is that the marginal effect of a given increase in the probability of getting caught should be increasing in the fine, (or alternatively that the marginal impact of the fine should be increasing in the probability of getting caught.) The results are reported in Table 6. As before, all standard errors are clustered at the individual-level. Columns (1) and (2) report the results of the models that employ the high school sample and the full sample, respectively. The estimated coefficients are almost identical in both samples. As expected, the interaction term between the probability of getting caught and fine is negative and statistically significant. Using the estimates in column (2) we find that the impact on the propensity to steal of a one-percentage point rise in the probability of getting caught, evaluated at the mean value of fine ($2.12) is equal to −0.003 (0.001–0.002×2.12). This means, for instance, that a five percentage point increase in the probability of detection lowers the propensity to steal by 1.5 percentage points if the amount of the fine is $2. If the penalty for stealing is $3, the same five-percentage point

[10] This is consistent with the results of Mocan (2013).

[11] Adjusting for age, height could be a proxy of the uterine environment (including disease and mother's nutrition intake) and childhood nutrition and therefore a marker for cognitive ability (see Case and Paxson 2008; Resnik 2002, and literature they cite).

[12] In these specifications, the variable *Oldest Child* is coded as 1 if the person has no siblings. Alternatively, assigning the value of zero to *Oldest Child* when the person is the only child had no impact on the results. Excluding the *Oldest Child* variable did not change the results either.

Table 6 The impact of rewards and sanctions on the propensity to steal (with interaction)

Variable	(1)	(2)	(3)	(4)
Loot	0.065***	0.067***	0.099***	0.090***
	(0.009)	(0.009)	(0.011)	(0.010)
Probability of getting caught	0.0003	0.001	0.0001	−0.007***
	(0.0009)	(0.001)	(0.001)	(0.001)
Fine	0.038**	0.045***	0.073***	−0.097***
	(0.017)	(0.015)	(0.021)	(0.012)
Probability x Fine	−0.002***	−0.002***	−0.003***	
	(0.0003)	(0.0003)	(0.0005)	
Age			0.0121	0.011
			(0.029)	(0.028)
Male			0.364***	0.322***
			(0.085)	(0.070)
Height			−0.189	−0.156
			(0.137)	(0.123)
GPA			0.050	0.048
			(0.078)	(0.076)
Endowment			−0.005	−0.004
			(0.009)	(0.009)
Money			0.001	0.001
			(0.002)	(0.002)
Years in Eugene			−0.017*	−0.014*
			(0.009)	(0.008)
One Sibling			0.059	0.069
			(0.143)	(0.143)
Two or more siblings			0.277*	0.269*
			(0.148)	(0.143)
Oldest child			−0.008	0.003
			(0.069)	(0.068)
Sample	High School	Pooled	High School	High School
Individual FE	Yes	Yes	No	No
R-square	0.14	0.20	0.25	0.25#
N	2,509	3,402	2,368	2,368

Standard errors, reported in parentheses, are clustered at the individual level. Statistical significance of the coefficients at the 10 %, 5 % and 1 % level are indicated by *, **, and ***. Models in columns (1)-(3) are estimated by OLS. Column (4) reports the average marginal effects obtained from maximum likelihood probit. The estimated probit model includes an interaction term for (probability of getting caught) x (fine). The reported marginal effects of the probability of getting caught and the fine implicitly include the impact of the interaction term. # represents the pseudo-R square value

increase in the probability of detection generates a decline in the propensity to steal by 2.5 percentage points. A one dollar increase in the penalty reduces the propensity to steal by 3.5 percentage points if the probability of getting caught is 40 %. However, if the probability of getting caught is 50 %, the same one-dollar increase in fine generates a decline in theft propensity by 5.5 percentage points.

Columns (3) and (4) of Table 6 report the estimation results of the model using the high school sample and with the addition of personal characteristics of the individuals. Column (3) displays the estimated coefficients from the linear probability model, and column (4) shows the marginal effects obtained from probit. The entries in column (4) represent the average marginal effect of the corresponding variable on the propensity to steal. The impact of the interaction term is implicitly incorporated into the probability of getting caught and into the fine variable when calculating the marginal effects.

Table 7 displays these impacts in a compact fashion. The Panel A of Table 7 reports the marginal impact of the fine, obtained from both the linear probability specification (column 3) and the probit specification (column 4) that employ the high school sample, when the probability of getting caught ranges from 35 % to 65 %. An increase in the certainty of punishment, represented by higher chances of getting caught, increases the impact of the fine.

Panel B of the table reports the exercise from the other angle, and displays the calculated impact of an increase in the certainty of punishment when the severity of

Table 7 The effect of certainty and severity of punishment (high school sample)

	Panel A				
	Linear Probability Model				
	Probability of Getting Caught				
	35 %	45 %	55 %	65 %	
$\frac{\partial(Prob\ \ of\ \ Theft)}{\partial(Fine)}$	−0.039***	−0.071***	−0.103***	−0.135***	
	(0.010)	(0.010)	(0.012)	(0.015)	
	Probit				
	Probability of Getting Caught				
	35 %	45 %	55 %	65 %	
$\frac{\partial(Prob\ \ of\ \ Theft)}{\partial(Fine)}$	−0.039***	−0.071***	−0.096***	−0.113***	
	(0.011)	(0.010)	(0.010)	(0.011)	
	Panel B				
	Linear Probability Model				
	Fine				
	\$1	\$1.5	\$2	\$2.5	\$3
$\frac{\partial(Prob\ \ of\ \ Theft)}{\partial(Prob\ \ of\ \ Getting\ \ Caught)}$	−0.003***	−0.005***	−0.006***	−0.008***	−0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	Probit				
	Fine				
	\$1	\$1.5	\$2	\$2.5	\$3
$\frac{\partial(Prob\ \ of\ \ Theft)}{\partial(Prob\ \ of\ \ Getting\ \ Caught)}$	−0.003***	−0.005***	−0.006***	−0.007***	−0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

The entries are the changes in the probability of stealing as fine goes up by \$1, or as the probability of getting caught goes up by 1 percentage point based on models in columns (3) and (4) of Table 6. The standard errors are calculated using the Delta method punishment gets bigger. The deterrent effect of the probability of getting caught gets bigger as the severity of punishment (represented by the magnitude of the fine) gets larger.

Table 8 presents the results of the same exercise, but in this case, we use the entire sample (high school student and college students). As in Table 7, the results are based on two specifications: the linear probability model reported in column 2 of Table 6, and the corresponding probit model. The results are very similar to those displayed in Table 7. The impact of the penalty gets larger as the probability of detection is higher. Similarly, the impact of the probability of detection gets larger as the penalty increases.

In order to investigate whether the results differ between the individuals who stole more frequently and those who did not steal as frequently, we re-estimated the models using only the individuals who stole six or fewer times during the experiment, and then using those who stole 7-to-13 times. Table 9 presents the marginal effects obtained from both the linear probability and the probit models in the sample of frequent stealers (those who decided to steal more than six times during the experiment) as well as less-frequent stealers. The marginal effects of the probability of getting caught and the fine are always negative. As before, the impact of the certainty (severity) of punishment gets larger as

Table 8 The effect of certainty and severity of punishment (pooled sample)

	Panel A				
	Linear Probability Model				
	Probability of Getting Caught				
	35 %	45 %	55 %	65 %	
$\frac{\partial(Prob\ \ of\ \ Theft)}{\partial(Fine)}$	−0.032***	−0.054***	−0.076***	−0.098***	
	(0.007)	(0.008)	(0.009)	(0.011)	
	Probit				
	Probability of Getting Caught				
	35 %	45 %	55 %	65 %	
$\frac{\partial(Prob\ \ of\ \ Theft)}{\partial(Fine)}$	−0.028**	−0.068***	−0.103***	−0.128***	
	(0.009)	(0.009)	(0.009)	(0.010)	
	Panel B				
	Linear Probability Model				
	Fine				
	$1	$1.5	$2	$2.5	$3
$\frac{\partial(Prob\ \ of\ \ Theft)}{\partial(Prob\ \ of\ \ Getting\ \ Caught)}$	−0.002***	−0.003***	−0.004***	−0.005***	−0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	Probit				
	Fine				
	$1	$1.5	$2	$2.5	$3
$\frac{\partial(Prob\ \ of\ \ Theft)}{\partial(Prob\ \ of\ \ Getting\ \ Caught)}$	−0.003***	−0.005***	−0.006***	−0.008***	−0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

The entries are the changes in the probability of stealing as fine goes up by $1, or as the probability of getting caught goes up by 1 percentage point. The specification is the one reported in column (2) of Table 6, and it is estimated by both OLS and probit. Standard errors are calculated using the Delta method the severity (certainty) goes up. It is interesting to note that, although the marginal effects are somewhat larger in the sample of those who stole more frequently, the elasticity of theft with respect to fine and with respect to the probability of getting caught is larger in the sample of less-frequent thefts. This is primarily because the baseline propensity to steal is lower in the group of people who did not steal as frequently. This means that a given percentage-point decline in the propensity to steal is translated into a larger percent change and therefore a larger elasticity. For example, in Panel A of Table 9 we see that when the probability of getting caught is 45 %, the marginal effect of the fine is about −0.07 among those who stole more than six times, and it is −0.03 among those who stole less than seven times. However, the *elasticity* of theft with respect to fine is −0.28 in the former group, while it is −1.98 in the latter group.

Discussion and Conclusion

The extent to which criminals and potential criminals respond to variations in deterrence is an important issue, both theoretically and from a public policy perspective. Despite significant progress in recent empirical analyses in identifying the causal effect of deterrence on crime, objections are still raised on the validity of methods proposed to eliminate the simultaneity between crime and deterrence in empirical analyses, and some social scientists continue to argue that criminal activity does not respond to sanctions. The issue is important because it involves fundamental arguments about the rationality of individuals in their decisions to engage in illegal acts and whether individuals respond to changes in the costs of crime, such as the probability of punishment and the penalty they face, if caught.

In this paper we analyze individuals' responses to potential criminal opportunities and the associated costs in an experimental setting. In our experiment subjects are exposed to exogenous variations in the relative tradeoffs between three important aspects of criminal opportunities – the amount of money they can steal from another person, the probability of getting caught, and the penalty (fine) they pay if caught. We conducted the experiment with juveniles and young adults, age groups that are near the peak ages for participation in petty crime and who are frequently labeled as "irrational" and "unresponsive to deterrence."

The instructions of the experiment employed loaded language, using the words "criminal," "victim," "stealing," "getting caught" repeatedly, to explicitly underline the dishonest nature of the act. The experimental design always gave the option of not stealing. We find that the propensity to steal responds to exogenous variations in the amount of money available to steal, and in the certainty and severity of punishment. An increase in the probability of getting caught reduces the propensity to steal, and the same is true for an increase in the size of the penalty. The elasticity of theft with respect to the fine is bigger than the elasticity with respect to the probability of getting caught. Furthermore, the impact of the certainty of getting caught is larger when the penalty is bigger. Similarly, the deterrent effect of the penalty is bigger when the probability of getting caught is bigger.

The caveats are that the "criminals" in these experiments are not necessarily criminals outside the laboratory, and that the crimes do not involve very large financial gains or

Table 9 The effect of certainty and severity of punishment by frequency of stealing (pooled sample)

	Panel A				
	Frequent Theft (>6)				
	Linear Probability Model				
	Probability of Getting Caught				
	35 %	45 %	55 %	65 %	
$\frac{\partial(Prob\ \ of\ \ Theft)}{\partial(Fine)}$	−0.034*** (0.010)	−0.065*** (0.009)	−0.096*** (0.010)	−0.128*** (0.012)	
	Probit				
	−0.034** (0.012)	−0.078*** (0.011)	−0.121*** (0.009)	−0.156*** (0.007)	
	Less Frequent Theft (<7)				
	Linear Probability Model				
	Probability of Getting Caught				
	35 %	45 %	55 %	65 %	
$\frac{\partial(Prob\ \ of\ \ Theft)}{\partial(Fine)}$	−0.021** (0.010)	−0.026*** (0.010)	−0.031*** (0.010)	−0.037*** (0.011)	
	Probit				
	−0.024** (0.011)	−0.031*** (0.011)	−0.031*** (0.011)	−0.028*** (0.011)	
	Panel B				
	Frequent Theft (>6)				
	Linear Probability Model				
	Fine				
	$1	$1.5	$2	$2.5	$3
$\frac{\partial(Prob\ \ of\ \ Theft)}{\partial(Prob\ \ of\ \ Getting\ \ Caught)}$	−0.001 (0.001)	−0.003*** (0.001)	−0.004*** (0.001)	−0.006*** (0.001)	−0.007*** (0.001)
	Probit				
	−0.002** (0.001)	−0.004*** (0.001)	−0.006*** (0.001)	−0.009*** (0.001)	−0.011*** (0.001)
	Less Frequent Theft (<7)				
	Linear Probability Model				
	Fine				
	$1	$1.5	$2	$2.5	$3
$\frac{\partial(Prob\ \ of\ \ Theft)}{\partial(Prob\ \ of\ \ Getting\ \ Caught)}$	−0.002*** (0.001)	−0.002*** (0.001)	−0.003*** (0.001)	−0.003*** (0.001)	−0.003*** (0.001)
	Probit				
	−0.002*** (0.001)	−0.002*** (0.001)	−0.002*** (0.001)	−0.002*** (0.001)	−0.002*** (0.001)

The entries are the changes in the probability of stealing as fine goes up by $1, or as the probability of getting caught goes up by 1 percentage point. The specification is the one reported in column (2) of Table 6, and it is estimated by both OLS and probit. Standard errors are calculated using the Delta method

losses, and because of the anonymity they do not involve social sanctions. Given these qualifications, these results demonstrate that individuals' decisions to commit crime are consistent with the predictions obtained from economic models, in that exogenous changes in enforcement and penalties do alter criminal behavior.

Appendix – Protocol

Welcome:

Today we are conducting an experiment about decision-making. Your decisions are for real money, so pay careful attention to these instructions. This money comes from a research foundation. How much you earn will depend on the decisions that you make, the decisions of others, and on chance.

Secrecy:

All your decisions will be secret and we will never reveal them to anyone. We will ask you to mark your decisions on paper forms using a pen or pencil. If you are discovered looking at another person's forms, or showing your form to another person, we cannot use your decisions in our study and so you will not get paid. Please do not talk during the experiment.

Payment:

You have been given a packet. Stapled to this packet is a card with a number on it. This is your claim check number. Each participant has a different number. Please tear off your card now. Be sure that your claim check number is written on top of the first page of your packet, but do not turn the page until instructed to do so. Be sure to keep your claim check number. You will present this number to an assistant in exchange for your payment envelope.

The Experiment:

You are going to play a game today. In this game you will be randomly and anonymously paired with another person in the room. One of you will be the criminal, and the other will be the victim. You will not know who you are paired with, even after the game is over.

Each person will start with some money, but the amount of money each person gets may be different. You will start with either \$16, \$12, or \$8. Your starting endowment has been determined randomly. The amount you start with is recorded on your packet.

The criminal will have a chance to steal some of the victim's money. However, stealing is not without a risk. If the criminal decides to steal some of the victim's money, there is a chance that the criminal is caught. If the criminal is caught, then he or she will have to return the money taken from the victim, and also pay a fine to the experimenter. The chance that the criminal is caught, and the amount of the fine, depend on the choice made by the criminal.

Everyone received one packet, and each packet contains 13 different sheets stapled together. We will show you an example. We call these Choice Sheets.

On each Choice Sheet everyone will make a choice as if you are the criminal. You will declare your choice of how much money to steal from the victim by putting a check mark next to one of the choices.

When we play the game the amount of money you will end up with will really be determined by the choices you make, so you want to consider your choice very carefully. We will give you 60 seconds on the first page and 30 seconds on each subsequent page. Please leave your pen on the desk and do not mark your choice until

I ask you to do so. When the time is up I will ask you to place a check mark next to the choice you want. It is important that you wait until the time is up to mark your choice.

After everyone has made a choice on each of the 13 Choice Sheets, you will have a chance to reconsider each of your decisions just to make sure you have considered each choice carefully. If you wish to change your decision, please cross out your old decision and mark your new decision with a red pen. We will give you 30 seconds on the first page and 15 seconds on each subsequent page. Please leave your pen on the desk and do not mark your choice until I ask you to do so. When the time is up I will ask you to place a check mark next to the choice you want. It is important that you wait until the time is up to mark your choice.

Next we have to determine who will be the criminal and who will be the victim. We randomly assign roles by flipping a coin. If it comes up heads, then those whose claim check number is even will be assigned the role of the criminal, and those whose claim check number is odd will be assigned the role of the victim. Should the coin come up tails, then those whose claim check number is odd will be assigned the role of the criminal, and those whose claim check number is even will be assigned the role of the victim.

Now we have to pick which one of the 13 Choice Sheets will count. We will pick a random number from 1 to 13, by having your teacher draw a card from a deck of 13 cards. The Ace will stand for 1, the Jack, Queen, and King will stand for 11, 12, and 13 respectively. The number of the card will determine which Choice Sheet counts. We will have you turn your packet to that choice sheet.

Note that you don't know which of your 13 decisions will count before you make all of your decisions, if any. This will be determined purely by chance. So, the best thing for you to do is to treat every choice sheet as if it will count, and make the choice on that sheet that you most prefer.

In the final step of the game we have to determine whether or not the criminal is caught. Here is how this will work: We have 4 index cards. On each index card there is a percentage written. They are: 25 %, 50 %, 75 % and 100 %. We will randomly choose one of these index cards. Everybody looks at their choice on the Choice Sheet that has just been selected. If you are the criminal, and if the percentage written on the selected index card is less than or equal to the chance of being caught for the choice you made on the Choice Sheet, then you are caught. You will have to return the money you stole from the victim and pay the corresponding fine to the experimenter. Otherwise you keep the money.

Now we will collect your decision packets and calculate your payments. To calculate your payments, we will randomly match one criminal with one victim. To get your envelope, we will ask you to fill out a receipt to be returned to us.

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