AN EXPERIMENTAL TEST OF CRIMINAL BEHAVIOR AMONG JUVENILES AND YOUNG ADULTS

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I. Introduction

Since the seminal paper of Becker (1968), which created the foundation for the economic analysis of criminal behavior, economists extended the basic theoretical framework (e.g. Ehrlich (1973, Block and Heineke 1975, Schmidt and Witte 1984, Flinn 1986, Lochner 2004, Mocan et al. forthcoming). The original framework as well as its more recent variants of this work postulate that participation in crime is the result of an optimizing individual's response to incentives such as expected payoffs of criminal activity and the cost of criminal activity such as the probability of apprehension and the severity of punishment.

Even though early research reported evidence that enhanced deterrence reduces crime (Ehrlich 1975, Witte 1980, Layson 1985), other papers found no significant evidence of deterrence (Myers 1983, Cornwell and Trumbull 1994). The main challenge in empirical analyses has been to tackle the simultaneity between criminal activity and deterrence. Specifically, an increase in criminal activity is expected to prompt an increase in certainty and severity of punishment (e.g. an increase in the arrest rate and/or the police force), which makes it difficult to identify the causal impact of deterrence on crime.
There have been three types of responses to overcome the simultaneity problem. The

first solution is to find a good instrument which is correlated with deterrence measures but uncorrelated with crime. Examples are Levitt (1997) which uses electoral cycles as an instrument for police hiring and Levitt (2002) which uses per capita municipal firefighters as an instrument for police. The second strategy is to use high-frequency time-series data. For example, in monthly data, an increase in police in a given month will impact criminal activity in the same month, but an increase in crime cannot alter the size of the police force in that same month, because it takes at least six months between a policy decision and the deployment of police officers on the street. This identification strategy has been employed by Corman and Mocan (2005) and Corman and Mocan (2000). The third strategy is to find a natural experiment which generates a truly exogenous variation in deterrence, such as in Di Tella and Schargrodsky (2004) which uses the increase in police protection around Jewish institutions in Buenos Aires after a terrorist attack to identify the impact of police on car thefts.

Although these empirical strategies refined and improved the estimates, to find a convincing natural experiment is a very difficult task, the validity of any instrumental variable can be questioned, and one can argue that if policy makers have perfect foresight about future crime, monthly data would also suffer from simultaneity.

In this paper we use a laboratory experiment to collect data on responses to unambiguously exogenous changes in the rewards and penalties pertaining to criminal behavior. The experiments involve decisions that are best described as petty larceny, and are done using high school students and real money. We use a straightforward protocol for collecting choice data that can be used to directly test Becker's model. The protocol does this by collecting data on (nearly) simultaneous choices under a variety of different budget constraints. The basic idea is to use these data to check if people's choices about their criminal behavior change rationally in response to changes in the probability of detection and the fine.

The data are first used to check for transitivity violations. Transitive choices would indicate that choices over the goods can be represented by utility maximization. This provides a direct test of Becker's model, which assumes rational choice by criminals. Next, we estimate demand functions. Becker (1962) points out that rational choice is not necessary for choices to satisfy the laws of demand. More fundamentally, aggregate choices may obey the laws of demand even if some individual choices are inconsistent with utility maximization. Therefore, we expect to be able to provide results about these tradeoffs even if choices sometimes, or even frequently, violate the Generalized Axiom of Revealed Preference (GARP).

We begin the paper with a discussion of revealed preference and experimental methods for testing it. We then analyze our data for consistency with GARP. We then estimate demand function for the amount of loot stolen. A discussion section concludes.

II. Experimental Tests of Revealed Preference and the Design

In this section we provide simplified discussion of revealed preference theory, one which relies on the assumption of continuous budget sets. Harbaugh et al. (2001) give the argument for the case of discrete choice sets, which were used in the experiment of this paper.[1]

The basic principle of the experiment can be seen in figure 1. Choices *a* and *b* are irrational by the following argument. When *a* was picked from the budget set *A*, the alternative *b* was within that set. So if this person was choosing rationally then $u(a) \geq u(b)$. Because of monotonicity and continuity, we can strengthen this statement to indicate $u(a) > u(b)$, because an alternative bundle with more of at least one good (actually both) than *b* is available within choice set *B*. By the same argument, we also know $u(b) > u(a)$. This is a contradiction. Thus, a person who made these choices could not have been choosing rationally. This is shown formally in Samuelson (1938), who shows that choices which are consistent with the Weak Axiom of Revealed Preference (WARP) are a necessary requirement for data that comes from maximizing a utility function.

This example only uses 2 choice sets, so we need only make direct comparisons. In our experiment we collect choices from 10 choice sets. Therefore, in addition to the above

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[1] In particular, Harbaugh et al. (2001) explain why strong monotonicity of preferences needs to be assumed with discrete choice, rather than the weaker assumption of local non-satiation.

direct tests of Strong Axiom of Revealed Preference (SARP), we can also test for chains of irrational choices that involve indirect comparisons, such as when choices reveal $u(a) > u(b) > u(c) > u(a)$. Houthakker (1950) showed that choice data which do not reveal these sorts of intransitivities, that is which satisfy SARP, are a necessary condition for rational choice; and Afriat (1967) showed that satisfying SARP was sufficient as well. Varian (1982) further generalized revealed preference, to allow indifference curves to have flat spots. His result on the equivalency of utility maximization and satisfying revealed preference is known as the Generalized Axiom of Revealed Preference (GARP). The complete protocol for our experiment is included in Appendix A. We construct choice sets from budget sets defined over three goods: stolen loot, the probability of not getting caught, and the amount one gets to keep, after the fine, if one is caught. We make up 10 different choice sets, each consisting of a list of between 7 and 14 bundles of these three goods. Each of these choice sets can be thought of as a menu of criminal opportunities, and each bundle can be thought of as a different crime – that is, some bundles will involve taking a little money, facing a low probability of detection, and a modest fine if caught, while others will involve a higher amount of loot, but a higher probability of detection, and so on. Taking nothing is always an option.

The list of bundles for each choice set are constructed with different implicit prices and incomes. The prices can be thought of as the rates of tradeoff between loot, the probability of not getting caught, and the smallness of the fine if you are caught. That is, a high implicit price for loot relative to the price of the probability of getting caught means that, in this choice set, choosing a crime with lots of loot will cost dearly in terms of the chances of getting caught. Incomes can be thought of as the overall extent of criminal opportunities available. A higher income means that, relative to a low income choice set, there are crimes available that involve not only lots of loot, but also low probabilities of detection, and small fines if caught.

The prices and incomes are chosen to ensure that the choice sets intersect frequently, with the intersections designed in such a way as to ensure many possibilities for intransitive choices. We include bundles on the frontier of the budget set, and also some interior bundles to check for monotonicity of preferences. Table 1A gives summary information on the choice sets and Table 1B gives the bundles for a representative choice set.

The participants are told that they must choose one bundle from each choice set. After 10 rounds (10 different choice sets), they and their partner have made their choices, we randomly determined whose choice is implemented – that is, who is the criminal and who is the victim. Also, one of the criminal's choice sets is randomly chosen, and whatever choice they made from that set is implemented. We use a randomized procedure to determine if they get away with any "crime" they might have chosen, or if they are instead caught and must return any loot to the victim and also pay the fine. The criminal and the victim are then paid the resulting amounts, in cash. Assuming that people's choices under uncertainty obey independence, this procedure gives everyone an incentive to make the choice from each choice set that they prefer the most.

Our protocol is designed to make sure that choices are made carefully, and that people can change their minds after thinking things over. We also perform a simple test of whether or not independence holds in this context. First, we give people 30 seconds to chose a bundle from each of the 10 choice sets. We tell them not to go on to the next choice set until 30 seconds are up. We call the 10 choices they make here their first choices. For the second choices, we have them go through the list again, spending 15 seconds on each list, and marking any changes they would like to make by crossing out the old and circling the new.

We test for independence by giving them another chance to change their minds, after the uncertainty about their role and the actual choice set is resolved. After the second choices, we tell them whether they are the criminal or the victim, and have them go through the choice sheets yet again. Finally, we tell them which choice sheet has been chosen to be implemented, and they can then change their choice on that sheet, if they wish. Choice sets are presented starting with the low income version, and going to high. The order of choices within the choice sets is blocked, with half the participants receiving forms where the loot choices go from low to high as you go down the page, and half vice versa.

Participants are recruited from math classes at a high school in Eugene, Oregon. After obtaining permission from the school district and the Principal, we contacted one teacher and performed the experiments in all of that teacher's classes. Students are matched with other students in their class, so they know the other participants quite well – although all interactions and payoffs are anonymous and secret. Because 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 that is richer and whiter than the US as a whole. We also recruit subjects from an upper division undergraduate industrial organization course at the University of Oregon. These students clearly differ from the high school students in many ways.

III. Revealed Preference Results

About 75% of participants change at least one choice for round 2, about 20% for round 3, and no one changes in round 4. We take this as evidence that choice behavior under the uncertainty, which is resolved in rounds 3 and 4, generally obeys independence. This is important, since independence is a necessary requirement for our protocol to generate data that can be used to test rationality.

We check for revealed preference violations using an algorithm which we modified from that in Varian (1995) to handle three goods and discrete bundles. Tests of SARP and WARP yield comparative results that are very similar to those from GARP, so only results for GARP are reported here. Table 2 displays the average number of GARP violations for high school subjects, college subjects, and all subjects, and provides a comparison to random (uniform and bootstrap) choice. In the bootstrap random choice, each bundle is weighted by its frequency in the overall choice distribution.

Each subject group exhibits significantly fewer violations than random choice or bootstrap choice. The average number of GARP violations across all classes is 4.2 violations. Table 2 gives frequencies for the number of GARP violations per subject. Note that, since a minimum of two choices are required to check for a transitivity violation, it is impossible to have just one violation. Overall, about 40% of the subjects have no GARP violations. All these reported numbers are for the final choices. The average number of violations in round 1 is about 4.8, so on average the changes that people make are moving them towards more rationality.

There is no obvious standard to compare the number of violations against. The revealed preference theorems described above require that choices obey the axioms without exception. In practice, this standard is not met. Sippel (1997) used a similar protocol to study rational choice by college students for 8 different consumption goods, using 10 different budget sets. He found that 24 of 42 participants violated GARP at least twice. Andreoni and Miller (1998) examined 142 college students' decisions about how much money to keep for themselves and how much to share with another, under 8 different budget constraints. They found that 9 percent of the participants had some violations of the revealed preference axioms. Harbaugh et al. (2001) looked at decisions over 2 consumption goods and 11 choice sets. Eleven-year-olds and college students had similar patterns, with about 35% having GARP violations. The average number of violations was about 2. The task in our experiment is more difficult in terms of number of goods than that in the Andreoni or Harbaugh experiments, but simpler than that of Sippel. On this basis, our results seem consistent with those generated by other experiments.

As in Harbaugh, Krause, and Berry (2001) and Andreoni and Miller (2002), our revealed preference test requires that preferences are strongly monotonic. Rather than take this on faith, our experiment is designed to test this assumption by including dominated bundles in the choice set – that is, bundles with lower loot and/or higher probabilities of detection and fine. Table 3 gives the frequency of the number of monotone choices for our sample, and compares this to a Monte Carlo simulation with 10,000 sets of uniform draws from our choice sets. The average number of monotone choices is 7.0, and exactly half of our 106 participants made 8, 9, or 10 monotone choices. This is compared to 13% under the Monte Carlo simulation.

Sippel (1997) reports that most of his participants spent their entire budgets, and those who didn't were very close to spending it all. The Harbaugh et al. (2001) paper simply assumes monotonicity, but does not include any procedure for checking it. Andreoni and Miller (2002) have a significantly larger percentage of monotone choices (88%) than we find. Our experiment involved a significantly greater number of alternatives, and our monotonicity test was integrated into each budget set, while the Andreoni paper constructed separate budget sets specifically for the purpose of testing for monotonicity. It seems likely that this procedure makes the non-monotonic choices more obvious and less likely to be chosen.

We attempted to explain the relationship between the rationality of choices of the participants and their characteristics. Definitions and descriptive statistics of the variables are provided in Table 4. Oldest Child is a dichotomous variable to indicate if the subject is the oldest child in his/her family. In case of no siblings, the subject is considered as the oldest child. Tenure is the number of years the subject has lived in Oregon. A larger value may be considered as a proxy for enhanced tied to friends and community; therefore it may be negatively correlated with the propensity to steal.

Table 5 presents the results of the ordered probit regressions where the dependent variable is the number of GARP violations. The first column includes as explanatory variables the age, gender, GPA, and height of the individual, and whether he/she is a high school student, oldest child and the amount of money spent per week. The second column displays a more flexible specification where the explanatory variables are interacted with the High School dummy. Thus, the hypothesis of differential impact of the variables by high school vs. college status is entertained. The results show that among college students being older and having a higher GPA are associated with a reduction in the number of GARP violations, while the opposite is true for high school students. An increase in the money spent per week is associated with a reduction in GARP violations among college students. Gender, height and being the oldest sibling have no impact on the number of GRP violations of the individual. The general conclusion is that the rationality of behavior is not well explained by the available variables.

Rationality requires that choices over crimes obey the GARP. Although our data are not entirely consistent with this axiom, the number of violations is in line with what other researchers have observed for choices over general types of consumption goods. Thus, the observed behavior is at least broadly consistent with utility maximization.

IV. Crime and Deterrence

In this section of the paper we estimate demand functions for stolen money. Specifically, we investigate the determinants of the amount of loot stolen, as a function of personal characteristics of the person who steals, the price of the stolen loot, the probability of being caught, and the amount of fine. Table 6 presents the distribution of the number of thefts. During the 10 rounds of the experiment, each individual had the opportunity to steal 10 times. Thus, in Table 6, zero thefts means that the individual never stole during the experiment, and a 10 indicates that he/she stole money in every round. There is substantial variation in the number of thefts, with 49 percent of the subjects stealing in each round.

Each participant makes 10 different choices, each from a different choice set. These choice sets differ in terms of the available tradeoffs between loot, the probability of detection, and the fine. We define these tradeoffs in terms of implicit prices and incomes. In some choice sets there is a high implicit price for loot relative to the price of the probability of getting caught, so choosing a crime with lots of loot substantially increases the chances of getting caught. Incomes can be thought of as the overall extent of criminal opportunities available. A higher income means that, relative to a low income choice set, there are crimes available that involve not only lots of loot, but also low probabilities of detection, and small fines if you are caught.

If people are choosing rationally, then we would expect them to respond these changes in implicit prices in ways that are consistent with the laws of demand. For example, we'd expect that participants will respond to an increase in the cost of choosing a crime with high loot by tending to move toward crimes with less loot but also lower probabilities of detection and/or lower fines. An increase in the general extent of the available criminal opportunities should also be expected to increase loot, assuming it is a normal good. In these regressions, we normalize the implicit prices by dividing through by income. We expect therefore to find negative own price effects and positive cross price effects.

Table 7 displays the results where the decision to steal is analyzed. More specifically, columns I and II of Table 7 present the marginal probabilities of the explanatory variables pertaining to the decision at the extensive margin. In this analysis each individual contributes 10 observations because they make 10 decisions in 10 rounds regarding whether or not to steal. In these regressions the estimated coefficient of the price of detection is positive and significant as expected. The only other statistically significant variable is "Stole in t-1" which is a dichotomous variable to indicate if the person stole in the previous round (i.e. loot>0 in the previous round). As can be seen, stealing in the previous round has a positive impact on stealing in the next round. This result underscores potential path-dependence in criminal behavior.

In Column II, where potentially endogenous variables of Money, GPA and tenure are omitted, the age and height of the individual has a positive impact on the propensity to steal.

This may indicate that having stronger physical attributes may provide motivation to steal. Being the oldest child, on the other hand, lowers the propensity to steal.

Column III of Table 7 presents the estimated ordered-probit results. The categories are: stealing 0 or 1 time, 2-4 times, 5-7 times and 8-10 times during the course of the experiment. In this specification each individual contributes one observation, thus the impact of prices cannot be analyzed. The result are consistent with those reported in columns I and II, but only the coefficient of Age is estimated with precision.

Table 8 presents the results of the estimated demand functions. The dependent variable is the amount of loot taken in each round. Models are estimated with OLS, and standard errors are adjusted for clustering at the individual level. Column I reports the results where the amount of loot taken is explained by personal characteristics of the individual as well as the prices. For half of the subjects the potential loot amounts were listed in ascending order, for the other half they were listed in descending order. The variable "Ascending" controls for this potential impact. Column II of Table 8 is the same as column I, but it excludes Money, GPA, Ascending and Tenure from the model. The results are interesting. Older individuals steal more loot, and having stolen in the previous round generates an incentive to take more loot in the current round. All three prices are highly significant with expected signs. More specifically, an increase in the price of loot generates a reduction in the loot taken, and increases in detection and fine prices bring about increases in the loot taken.

Column III and Table 8 displays the results of the specification where the loot taken in each round is explained only by prices and theft in the previous round (Stole in t-1). This specification, which also includes individual fixed-effects, provides very similar price effects. Column IV is the same as column III, but the variable that indicates theft activity in the previous round is omitted. In this specification the price of fine becomes smaller and statistically insignificant.

Columns V to VII are obtained from models similar to those presented in I to III. The difference is the inclusion of the interaction terms between three prices and the High School dummy to investigate if college and high school students react differently to changes in prices. The first two rows of columns V-VII indicate that college students are more responsive to an increase in the price of loot. It should be noted, however, that the coefficient of loot price for high school students is still negative and statistically different from zero. Columns V and VI indicate that the coefficients of detection price and fine price are the same for college and high school students, although column VII suggests that the effects on the loot taken of variations in detection and fine prices may be smaller for high school students.

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 this paper we design an experiment where subjects are exposed to exogenous variations in the relative tradeoffs between three important aspects of criminal opportunities – lot, the probability of detection, and the fine. We conduct the experiment with juveniles and young adults (high school students and college students who are younger than 26 years of age), age groups that are frequently labeled as "irrational" and "unresponsive to deterrence".

We find that behavior among this group with respect to petty criminal decisions is not entirely rational. However, it is approximately as consistent with the theoretical requirements of rational choice behavior as choice behavior over consumption goods is. Furthermore, we find that, in aggregate, responses to changes in criminal opportunities are consistent with the laws of demand. Caveats are that the participants in these experiments are not necessarily criminals outside the laboratory, and that the crimes we experiment on involve small financial gains and losses. Given these qualifications, we believe these results strengthen the argument that criminal behavior and the response of criminals to changes in enforcement and penalties can be accounted for by economic models.

References

AFRIAT, S. N. (1967). "The construction of a utility function from expenditure data," *International Economic Review*, 7, 67-77.

ANDREONI, JAMES, and JOHN MILLER. (2002): "Giving according to GARP: an experimental test of the consistency of preferences for altruism," *Econometrica*, 70, 737-753.

BECKER, G. S. (1968), Crime and Punishment: An Economic Approach. *Journal of Political Economy*, **76**, 169-217.

BLOCK, M. and HEINEKE M. (1975), A Labor Theoretic Analysis of the Criminal Choice. *The American Economic Review*, 314-25.

CORNWELL, C. and TRUMBULL, W. N. (1994), Estimating the Economic Model of Crime with Panel Data. *Review of Economics and Statistics*, **76** (2), 360-366.

CORMAN, H. and MOCAN, N. (2000), A Time-Series Analysis of Crime, Deterrence and Drug Abuse in New York City. *American Economic Review*, **90** (3), 584-604.

CORMAN, H. and MOCAN, N. (2005), Carrots, Sticks, and Broken Windows. *Journal of Law and Economics (forthcoming)*

DIIULIO, J. J. (1996), Help Wanted: Economists, Crime and Public Policy. *The Journal of Economic Perspectives*, **10** (1), 3 - 24.

DI TELLA R. AND SCHARGRODSKY E., Do Police Reduce Crime? Estimates Using the Allocation of Police Forces After a Terrorist Attack, *American Economic Review*, **94** (1), 115-134.

EHRLICH, I. (1973), Participation in Illegitimate Activities: A Theoretical and Empirical Investigation. *Journal of Political Economy*, **81**, 521-565.

EHRLICH, I. (1975), The Deterrent Effect of Capital Punishment: A Question of Life and Death. *American Economic Review*, **65** (3), 397-417.

FLINN, C. (1986), Dynamic Models of Criminal Careers. (*In* Blumstein, A. et al. (eds.), Criminal *Careers and "Career Criminals".* Washington DC: National Academy Press)

HARBAUGH, WILLIAM T., KATE KRAUSE, AND TIMOTHY BERRY. (2001): "GARP for kids: on the development of rational choice behavior," *American Economic Review*, 91, 1539-1545.

HOUTHAKKER, H. S. (1950). “Revealed preference and the utility function.” *Economica*, 17: 159-74.

LAYSON, S. K. (1985), Homicide and Deterrence: A Reexamination of the United States Time-Series Evidence. *Southern Economic Journal*, **52** (1), 68-89.

LEVITT, S. D. (1997), Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime. *American Economic Review*, **87** (3), 270-290.

LEVITT, S. D. (2002), Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime: Reply." *American Economic Review*, **92** (4), 1244-1250.

LOCHNER, L. (2004), Education, Work, and Crime: A Human Capital Approach. International Economical Review (forthcoming).

SAMUELSON, PAUL. A. (1938). “A note on the pure theory of consumer’s behavior.” *Economica*, 5: 61-71.

SAMUELSON, PAUL. A. (1950): “Consumption theory in terms of revealed preference,” *Economica*, 15, 243-253.

SIPPEL, REINHARD. (1997). “An experiment on the pure theory of consumer’s behaviour,” *The Economic Journal*, 107, 1431-1444.

MOCAN H. M. and BILLUPS S. C. (2004), A Dynamic Model of Differential Human Capital and Criminal Activity. *Economica (forthcoming)*.

MYERS, S. L., Jr. (1983), Estimating the Economic Model of Crime: Employment Versus Punishment Effects. *Quarterly Journal of Economics*, **98** (1), 157-166.

SCHMIDT, P. and WITTE A. D. (1984), An Economic Analysis of Crime and Justice: *Theory, Methods and Applications*. Orlando, Florida: Academic Press.

VARIAN, HAL. (1982). “The nonparametric approach to demand analysis,” *Econometrica*, 50: 945-73.

VARIAN, HAL. (1995). “Efficiency in Production and Consumption,” working paper and Mathematica notebook. [Online]. Available: http://emlab.berkeley.edu/eml/nsf97/varian.pdf [2000, January 24]

WITTE A. D. (1980), Estimating the Economic Model for Crime with Individual Data. Quarterly Journal of Economics, February, 57-84.

Figure 1
Rational Choice and WARP

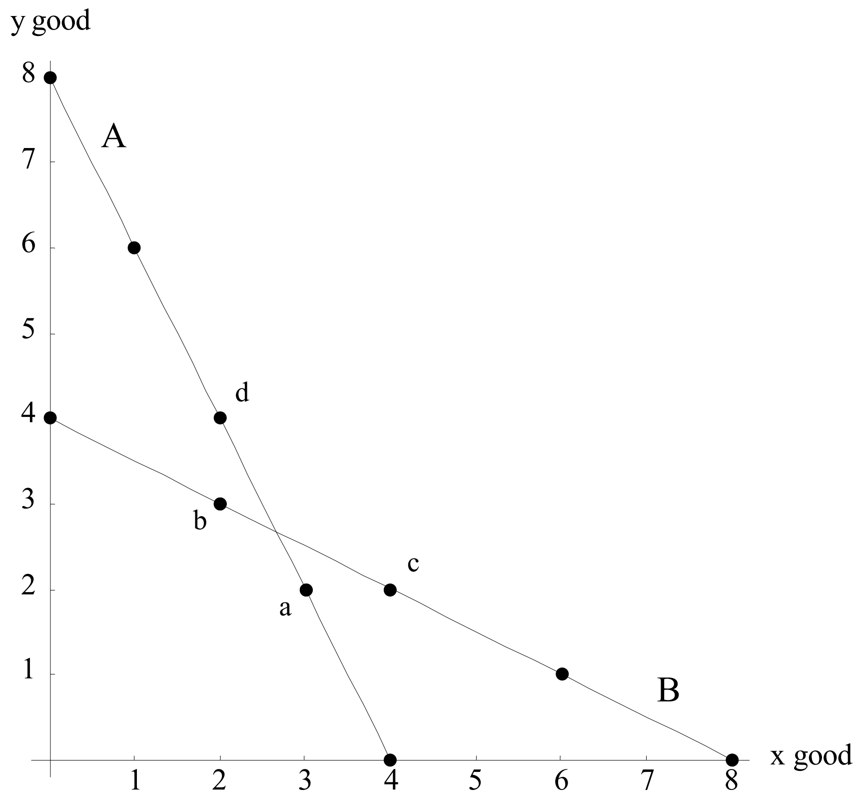

Table 1A
Choice Set Characteristics

Budget	loot_p	prob_p	nfine_p	income
	Budget parameters			
1	.25	1	1	1.2
2	1	2	1	2.9
3	.5	4	1	3.25
4	.5	2	1	2.25
5	.25	1	1	1.2
6	1	2	1	2.75
7	.5	4	1	3.25
8	.5	2	1	2.25
9	1	4	1	3.75
10	.25	2	1	1.75

Table 1B
Sample Bundles, from Choice Set 5

You each start with $5

Mark one choice below	Dollars to take from Person B	Your payment including your starting $5 if you are not discovered	Chance that you are discovered	Dollars paid to experimenter if discovered	Your payment including your starting $5 if you are discovered
	$0	$5	---	---	---
	$1.00	$6.00	25%	$1.55	$3.45
	$1.00	$6.00	50%	$1.30	$3.70
	$1.00	$6.00	75%	$1.05	$3.95
	$1.00	$6.00	75%	$1.25	$3.75
	$2.00	$7.00	50%	$1.55	$3.45
	$2.00	$7.00	75%	$1.30	$3.70
	$3.00	$8.00	75%	$1.55	$3.45

Table 2
Frequency of GARP Violations

Table 4.2 – Frequency of GARP Violations

Number of GARP violations	HS	UO	All	Bootstrap
0	37%	48%	40%	3%
1*	0%	0%	0%	0%
2	6%	0%	4%	3%
3	7%	0%	5%	5%
4	6%	0%	4%	6%
5	8%	10%	9%	10%
6	5%	6%	5%	16%
7	4%	6%	4%	20%
8	6%	6%	6%	21%
9	6%	10%	7%	14%
10	14%	13%	14%	4%
N	83	31	114	10,000

*Note that it is impossible to have exactly one violation.

Table 3
Monotonic bundle choices

Monotone Choices	Frequency	Running total	Monte Carlo	Running total
0	0%	0%	0%	0%
1	7%	7%	0%	0%
2	4%	11%	1%	1%
3	5%	16%	3%	4%
4	11%	26%	10%	13%
5	5%	32%	20%	34%
6	12%	44%	27%	61%
7	10%	54%	22%	83%
8	6%	60%	12%	95%
9	16%	75%	4%	99%
10	25%	100%	1%	100%
N	114		10,000	

Table 4
Descriptive Statistics

Variable	Definition	High School	College	All
Loot*	The money stolen in each round	1.23	1.77	1.38
		(1.14)	(1.21)	(1.19)
GARP	Number of GARP violations	4.01	4.00	4.01
		(3.84)	(4.16)	(3.91)
Age	Age of the individual	15.98	22.01	17.62
		(0.98)	(0.96)	(2.86)
Height	Height of the individual in feet	5.59	5.88	5.67
		(0.32)	(0.35)	(0.35)
GPA	High school GPA if the individual is in high school; the average of high school and college GPAs if in college	3.12	3.20	3.14
		(0.54)	(0.33)	(0.49)
Money	How much money the individual spends in his/her own per week	18.34	72.71	33.13
		(17.93)	(171.93)	(94.02)
Male	Dichotomous variable (=1) if the person is male	0.51	0.71	0.56
Oldest Child	Dichotomous variable (=1) if the person is oldest child	0.34	0.52	0.39
Tenure	The number of years the person lived in Eugene, Oregon	8.43	5.39	7.61
		(3.59)	(4.46)	(4.08)
n		83	31	114

*Loot is the average of all 10 rounds

Table 5
Ordered Probit Estimates
of the Number of GARP Violations

Variable	**I**	**II**
Age	0.041	-0.478*
	(0.109)	(0.274)
Age*High School	--------	0.627**
	--------	(0.300)
Male	-0.011	0.424
	(0.305)	(0.512)
Male *High School	--------	-0.372
	--------	(0.640)
Height	0.044	0.376
	(0.368)	(0.592)
Height *High School	--------	-0.700
	--------	(0.734)
GPA	-0.070	-1.659**
	(0.257)	(0.776)
GPA *High School	--------	1.723**
	--------	(0.828)
Money	-0.006	-0.014**
	(0.005)	(0.007)
Money *High School	--------	0.012
	--------	(0.010)
Oldest Child	-0.624***	-0.434
	(0.242)	(0.538)
Oldest Child *High School	--------	-0.248
	--------	(0.605)
High School	0.025	-14.590*
	(0.618)	(8.185)
n	114	114
Log-Likelihood	-214.82	-209.35

Robust standard errors in parentheses

*, ** and *** indicate 10, 5 and 1%significance levels respectively

Table 6

Number of Thefts*	Number of Individuals	Percentage of Total
0	5	4.39
1	2	1.75
2	2	1.75
3	4	3.51
4	6	5.26
5	2	1.75
6	6	5.26
7	6	5.26
8	13	11.40
9	12	10.53
10	56	49.12

***The number of thefts is the number of rounds where the individual stole money. Thus, 0 indicates that the individual did not steal money during the entire experiment and 10 indicates that he/she stole in every round.

Table 7
Participation in Crime

	Probit Estimates of Decision to Steal		Ordered Probit Estimates of the Number of Thefts
Variable	I[a]	II[a]	III
Loot Price	0.702	0.740	------
	(0.56)	(0.585)	------
Detection Pr.	0.460*	0.479*	------
	(0.247)	(0.255)	------
Fine Pr.	-0.020	-0.019	------
	(0.118)	(0.123)	------
Stole in t-1	0.333***	0.347***	------
	(0.037)	(0.039)	------
Age	0.032	0.036**	0.272**
	(0.021)	(0.018)	(0.131)
Male	-0.033	-0.020	-0.368
	(0.041)	(0.029)	(0.361)
Height	0.066	0.059*	0.599
	(0.045)	(0.039)	(0.476)
Money	0.001	------	0.005
	(0.001)	------	(0.005)
High School	0.099	0.090	1.214
	(0.156)	(0.138)	(0.834)
GPA	-0.016	------	-0.020
	(0.029)	------	(0.298)
Oldest Child	-0.041	-0.046**	-0.385
	(0.024)	(0.02)	(0.254)
Tenure	-0.005**	------	-0.033
	(0.002)	------	(0.035)
n	1026	1026	114
Log-likelihood	-408.98	-411.77	-96.13

The categories for the ordered probit model are 0-1 crimes, 2-4 crimes, 5-7 crimes and 8-10 crimes
Robust standard errors in parentheses
*, ** and *** indicate 10, 5 and 1%significance levels respectively
a) The reported coefficients are marginal probabilities

Table 8
Demand for Loot

Variable	I	II	III	IV[a]	V	VI	VII
Loot Price	-2.354**	-2.335**	-2.056**	-3.880***	-4.848***	-4.834***	-4.793***
	(1.015)	(1.015)	(1.040)	(1.131)	(1.553)	(1.559)	(0.968)
Loot Price*High School	------	------	------	------	3.448*	3.455*	1.254**
	------	------	------	------	(1.947)	(1.946)	(0.566)
Detection Pr.	1.485***	1.491***	1.578***	0.986**	1.336**	1.341**	1.435***
	(0.403)	(0.404)	(0.413)	(0.442)	(0.642)	(0.644)	(0.383)
Detection Pr.*High School	------	------	------	------	0.211	0.212	-0.615***
					(0.802)	(0.802)	(0.214)
Fine Pr.	0.604***	0.607***	0.651***	0.055	0.885***	0.888***	0.424
	(0.226)	(0.226)	(0.230)	(0.266)	(0.337)	(0.337)	(0.266)
Fine Pr.*High School	------	------	------	------	-0.382	-0.382	-0.506**
	------	------	------	------	(0.435)	(0.435)	(0.260)
Stole in t-1	0.534***	0.544***	0.691***	------	0.542***	0.552***	------
	(0.129)	(0.128)	(0.134)	------	(0.128)	(0.127)	------
Age	0.116**	0.114**	------	------	0.116**	0.113**	------
	(0.058)	(0.055)	------	------	(0.058)	(0.055)	------
Male	-0.059	-0.024	------	------	-0.059	-0.024	------
	(0.161)	(0.136)	------	------	(0.161)	(0.136)	------
Height	0.321	0.333	------	------	0.320	0.332	------
	(0.216)	(0.206)	------	------	(0.216)	(0.206)	------
Money	0.001***	------	------	------	0.001***	------	------
	(0.0002)	------	------	------	(0.0002)	------	------
High School	0.403	0.297	------	------	-0.434	-0.542	------
	(0.381)	(0.370)	------	------	(1.431)	(1.426)	------
GPA	-0.030	------	------	------	-0.030	------	------
	(0.123)	------	------	------	(0.123)	------	------
Ascending	0.125	------	------	------	0.126	------	------
	(0.105)	------	------	------	(0.105)	------	------
Oldest Child	-0.134	-0.087	------	------	-0.134	-0.086	------
	(0.112)	(0.117)	------	------	(0.112)	(0.117)	------
Tenure	-0.012	------	------	------	-0.012	------	------
	(0.013)	------	------	------	(0.013)	------	------
Constant	-4.165***	-4.249***	-0.470	1.302*	-3.560**	-3.641**	1.302**
	(1.590)	(1.516)	(0.745)	(0.784)	(1.796)	(1.732)	(0.605)
n	1026	1026	1026	1140	1026	1026	1140
Adjusted-R^2	0.26	0.25	0.21	0.14	0.27	0.25	0.18

Robust standard errors, which are adjusted for clustering at the individual level are in parentheses.
*, ** and *** indicate 10, 5 and 1%significance levels respectively
a: This model contains individual fixed-effects. The R-squared is the overall R^2.