Individual Perceptions of the Criminal Justice System

By LANCE LOCHNER*

Empirical estimates of deterrence are based on two distinct approaches: one estimates the effect of *actual* or official measures of certainty and severity of punishment (or factors like the number of police in an area) on crime; the other measures the effect of *perceived* certainty or severity of punishment on crime. Most studies of the former type conclude that deterrence effects are important, while studies of the latter type provide mixed results.[1] This paper contributes to the perceptions-based literature.

Many of the perceptions-based studies do not necessarily measure the effects of beliefs on actual criminal outcomes. Instead, they typically measure differences in intentions to commit crime or the likelihood that someone will engage in crime given a set of circumstances surrounding an opportunity. The vast differences in design across perceptual studies and the diverse findings make it difficult to draw any strong conclusions about the effect of a change in the perceived probability of arrest on actual criminal behavior. More importantly, Nagin (1998) recently noted that "While great effort has been committed to analyzing the links between sanction risk perceptions and behavior, comparatively little attention has been given to examining the origins of risk perceptions and their connection to actual sanction policy."[2]

The evolution of beliefs plays an important role in different theories of crime. Theories developed in Raj Sah (1991) and Lochner (2004) stress that when the probability of arrest is learned from others or through one's own experiences, the effects of policy tend to be lagged and long-lasting, even if policy changes are temporary. The "broken windows" theory of James Q. Wilson and George L. Kelling (1982) suggests that individuals are more likely to engage in crime in neighborhoods exhibiting decay (e.g., broken windows or abandoned buildings), because they believe they are less likely to be arrested or interfered with. Understanding the information used in forming beliefs and how perceptions influence behavior is central to these specific theories of crime and the general theory of deterrence.

This paper makes two contributions to the perceptions-based deterrence literature using self-reported beliefs about the probability of (one's own) arrest from two sources of longitudinal data (the National Longitudinal Survey of Youth 1997 Cohort, NLSY97, and the National Youth Survey, NYS). First, this paper examines which factors influence individual perceptions about the probability of arrest. In particular, it analyzes (a) the correlation between various demographic characteristics (e.g., race and ethnicity) and beliefs about the probability of arrest; (b) the correlation between local official arrest rates and perceptions; (c) the role of neighborhood conditions in determining beliefs; and (d) the role of new information and belief updating in determining perceptions about the probability of arrest. This paper shows that individuals update their beliefs in rational ways such that criminals who avoid arrest reduce their perceived probability of arrest, while those

* Lochner: Department of Economics, The University of Western Ontario, 1151 Richmond St., London, Ontario, N6A 5C2, Canada (e-mail: llochner@uwo.ca). For their comments, I thank Mark Bils, Elizabeth Caucutt, Gordon Dahl, Isaac Ehrlich, Andrew Foster, Bo Honore, Hiro Kasahara, Shakeeb Khan, Steve Levitt, Ray Paternoster, Greg Pogarsky, Jeff Smith, Todd Stinebrickner, two anonymous referees, and participants at numerous seminars and conferences.

[1] See Daniel Nagin (1998) for a recent survey of both literatures. Recent studies using actual police, arrest, or punishment measures include Jeffrey Grogger (1991), Joel Waldfogel (1993), Helen Tauchen, Ann D. Witte, and Harriet Griesinger (1994), and Steven D. Levitt (1997, 1998). Recent deterrence studies using perceived measures of certainty or severity include Ronet Bachman, Raymond Paternoster, and Sally Ward (1992), Nagin (1993), Raymond Paternoster and Sally Simpson (1996), and Greg Pogarsky and Alex Piquero (2003).

[2] Exceptions include Pamela Richards and Charles Tittle (1981), Linda Saltzman et al. (1982), Paternoster et al. (1983, 1985), Irving Piliavin et al. (1986), and Julie Horney and Ineke Haen Marshall (1992).

who are arrested increase their perceived probability.[3] Beliefs also respond to changes in the criminal histories of their siblings, but not to information about the arrest outcomes of their siblings or other random persons.

Second, this paper empirically examines the effects of individual beliefs about the probability of arrest on criminal behavior. By examining this relationship in large random national samples of young males, the results shed light on actual deterrence effects that might be expected when beliefs are changed through policy intervention. Consistent with deterrence theory, estimates suggest that a higher perceived probability of arrest reduces criminal participation. Consequently, individual heterogeneity in beliefs about the criminal justice system leads to differences in criminal participation.

I. The Evolution of Crime and Beliefs

Individuals hold beliefs about the probability of arrest for different types of crime and decide whether or not to engage in crime based on those beliefs. Their decision to commit crime and whether they are arrested affect their future beliefs about the probability of arrest. Beliefs may also respond to information from other sources. For example, individuals may observe crimes committed by others and whether or not they are arrested, as studied by Sah (1991). They may move from one neighborhood to another or observe more police on the street. Using all of this information, individuals continually form new beliefs and decide whether or not to engage in crime. Because ex ante identical agents receive different information about the probability of arrest, their beliefs and criminal behavior will likely differ at any point in time.

We now sketch a simple model of belief updating and criminal participation in order to guide the empirical analysis below and to highlight a few important policy implications. First, consider the decision to commit crime when there is uncertainty about the probability of arrest. Following Gary S. Becker (1968), assume that individuals choose to commit crime if the expected benefits exceed the expected costs. For simplicity, assume the benefits to each individual i from committing a crime at age t, B_{it}, are known beforehand. Individuals also know the punishment, $J_{it} \geq 0$, associated with an arrest, but they do not necessarily know their own probability of arrest. Instead, they have some beliefs about that probability (π_i), where we denote the expected probability of arrest conditional on information at date t, H_i^t, by $E(\pi|H_i^t)$. Assuming no intertemporal effects of arrest or criminal behavior (except through beliefs), individual i will commit a crime in period t if and only if $B_{it} > E(\pi|H_i^t)J_{it}$.[4]

Now, consider the evolution of beliefs. Beliefs about the probability of arrest are likely to depend on an individual's own (past) criminal behavior and arrest outcomes, the criminal and arrest outcomes of others around him, and more general signals that may come from local arrest rates or neighborhood conditions. Let c_{it} be an indicator equal to one if individual i commits a crime between (survey) dates $t-1$ and t, and zero otherwise. Similarly, let A_{it} be an indicator equal to one if he is arrested during that time period, and zero otherwise.[5] Let $\tilde{c}_{it}$ and $\tilde{A}_{it}$ rep-

[3] Early studies by criminologists that explore the link between perceptions and crime report that individuals engaged in crime tend to lower their perceived probability of arrest, referring to these effects as "experiential effects" (W. William Minor and Joseph Harry 1982; Saltzman et al. 1982; Paternoster et al. 1983; Piliavin et al. 1986). Horney and Marshall (1992) estimate a positive correlation between arrests per crime in recent years and current beliefs, but they cannot determine whether that correlation is due to belief updating or a strong correlation between initial (and, perhaps, stable) beliefs and observed outcomes. Studying 300 college students, Paternoster et al. (1985) offer some evidence that changes in the perceived probability of arrest are negatively correlated with criminal activity and positively correlated with formal sanctions. None of these studies takes into account the endogeneity of criminal behavior.

[4] This decision rule assumes individuals behave myopically and ignores any incentive to commit crime in order to learn more about the true probability. Incorporating this type of strategic behavior is straightforward and would create an additional incentive to engage in crime when beliefs are uncertain.

[5] The timing notation makes it easier to follow the empirical analysis below, since all variables with a t subscript are collected in the same survey (i.e., crime and arrests are retrospective since the previous survey, while beliefs are recorded at the time of the survey).

resent vectors of these indicators for individuals that person i associates with. Finally, we denote any new information about the local environment by Z_{it}. Information accumulates according to $H_i^t = (H_i^{t-1}, c_{i,t}, A_{i,t}, \tilde{c}_{i,t}, \tilde{A}_{i,t}, Z_{i,t})$. A fairly general rule for updating beliefs is given by

$$E(\pi|H_i^t)$$
$$= g(E(\pi|H_i^{t-1}), c_{i,t}, A_{i,t}, \tilde{c}_{i,t}, \tilde{A}_{i,t}, Z_{i,t}).$$

Now, consider a number of potential assumptions for this updating equation. First, the current perceived probability of arrest should be increasing in the previous expected probability ($g_1 \geq 0$).[6] Second, the expected probability of arrest should be decreasing in the number of crimes already committed (by oneself or others), holding the number of arrests constant ($g_2 \leq 0$ and $g_4 \leq 0$). Third, the total effect of committing a crime and getting arrested for it should lead to an increase in the expected probability of arrest (i.e., $g_2 + g_3 \geq 0$ and $g_4 + g_5 \geq 0$).[7] Fourth, one might expect that beliefs are increasing in actual local arrest rates. Fifth, the broken windows theory of Wilson and Kelling (1982) suggests that individuals are likely to think the probability of arrest is lower in communities with rundown buildings, broken windows, and rampant lawlessness. This paper empirically examines each of these potential assumptions.

Before turning to the empirical analysis, it is worth briefly discussing the implications of these assumptions for life-cycle criminal behavior and the evolution of beliefs. To begin, consider an individual who elects to commit a crime. If he avoids arrest, he will unambiguously lower his perceived probability of arrest (assuming no changes in other information). This will raise the likelihood that he commits crime the following period. On the other hand, if he is arrested, he should raise his expected probability of arrest, making him less likely to commit crime in the future. Thus, criminal profiles will be determined, in part, by the randomness associated with an arrest. The "lucky" individual who manages to avoid an arrest early on is more likely to continue committing crime thereafter than is the "unlucky" person who gets arrested.

Beliefs need not be accurate. In fact, criminals are likely to be optimistic in that they will tend to believe that their probability of arrest is lower than it actually is, while noncriminals will tend to be pessimistic about their chances of evading arrest. This is even true among those who start their criminal careers with unbiased prior beliefs. To understand why, suppose that all individuals begin with unbiased priors. Any change in beliefs, therefore, leads to a bias. Since individuals commit crime only if the expected probability is low enough, those who continue to engage in crime tend to be the lucky ones who have not been arrested for their past crimes. On average, they reduce their perceived probability of arrest leading to a systematic downward bias. At the other extreme, those choosing not to commit crime are likely to have started out with a very high perceived probability of arrest or to have experienced an arrest some time in the past, causing them to revise their beliefs upward. The latter subgroup of current noncriminals (but former criminals) will bias the average beliefs of all noncriminals upward. With homogeneity in the true probability of arrest and unbiased prior beliefs, criminals should, on average, underestimate the true arrest rate while noncriminals will tend to overestimate it.

When there is heterogeneity in the true probability of arrest across individuals, average beliefs about the probability of arrest will tend to be higher than official arrest rates, even if beliefs are unbiased for each individual. This is because those facing high probabilities of arrest (true and perceived) will not engage in crime. The opposite is true for those with low probabilities. Official arrest rates will be lower than the average probability in the population, since arrest rates reflect the probability of arrest only for those choosing to engage in crime. This difference will tend to be large when there is considerable heterogeneity in arrest probabilities.

[6] We denote the partial derivative of $g(\cdot)$ with respect to its kth argument by g_k.

[7] Contrary to these assumptions, the "gambler's fallacy" posits that someone who is not arrested may feel he is due to be arrested next time (and vice versa). Pogarsky and Piquero (2003) explore this hypothesis in regards to drinking and driving. Empirically, we find no evidence of this effect in either the NLSY97 or NYS data.

If individual beliefs depend only on policy-invariant priors and individual crime and arrest histories (i.e., individuals either do not hear about policy changes or do not believe such announcements), then a number of policy implications contrast sharply with those of standard models that assume the true probability of arrest is known. When individuals do not know the true probability of arrest, an increase in that probability (e.g., through an increase in police or more lax rules on police searches) should have no immediate effect on crime, but it should produce lagged effects. This is true of both permanent and temporary changes. Policy effects are lagged because they affect crime only indirectly through beliefs, which take time to evolve. Each additional arrest that results from a policy change will cause arrestees to revise their perceived probability of arrest upward. This increases the likelihood that they refrain from committing further crimes in the future. Even with a direct announcement effect on beliefs, the long-run effects of an increase in the probability of arrest would be greater than the short-run effects.[8] On the other hand, when the probability of arrest is known with certainty, all effects on crime are immediate and continue only as long as actual arrest rates remain high (absent any intertemporal complementarities in returns to crime).[9]

II. Crime and Perceptions

A. *Crime and Beliefs in the NLSY97*

The NLSY97 contains a sample of 9,022 individuals (4,621 males) age 12 to 16 in 1997. This study uses four years of panel data for males covering the years 1997 to 2000. Information relevant to this study includes data on family background, individual achievement test scores, neighborhood characteristics, criminal behavior, and perceptions about the probability of arrest for auto theft.[10]

The extent of criminal activity among young males in the NLSY97 is shown in Table 1. About 5.5 percent of young males report committing a theft of over $50 in any given year, with blacks reporting the most involvement and whites the least. Slightly more than 1 percent of the sample reports committing auto theft. Approximately 8 percent of all young males report an arrest for some offense in any year, but only 1.7 percent report an arrest for theft.

Unfortunately, the data do not allow us to determine what category or type of theft for which an arrest was made. To the extent that most arrests occur for thefts of something worth more than $50, we can approximate the arrest rate for theft by race/ethnicity. Between 0.28 (Hispanics) and 0.36 (black) individuals report an arrest (for theft) for every individual who reports having stolen something worth more than $50. A better measure for an arrest rate divides the total number of arrests for theft by the number of reported thefts of more than $50. These rates range from 0.06 for Hispanics to 0.12 for blacks.[11] While these rates are substantially lower than official clearance rates for burglary, larceny-theft, and motor-vehicle theft, they accurately reflect official arrest rates for theft after adjusting for nonreporting (to the police) by victims. Adjusted arrest rates for theft in 1997 are lowest for the general larceny-theft category (5.4 percent), slightly higher for burglary (7.6 percent), and highest for motor-vehicle theft (10.0 percent).[12]

[8] Consistent with this prediction, Hope Corman, Theodore Joyce, and Norman Lovitch (1987) find evidence for both delayed effects of an increase in arrests on crime and long-term effects of a temporary increase in arrests.

[9] The criminal justice literature commonly refers to two distinct types of deterrence: *general* and *specific.* General deterrence refers to the effects of criminal justice policy through general policy announcements or overall arrest probabilities, while specific deterrence refers to deterrence achieved through an individual's own interaction with the justice system. The latter is emphasized here.

[10] Specifically, the survey asks: "What is the percent chance you would be arrested if you stole a car?"

[11] A number of caveats should be noted. Some individuals may be arrested even though they have not committed a theft, and some arrests may be for thefts of less than $50 in value. Both of these cases would bias these arrest rates upward. Additionally, arrests and crimes are self-reported, and both may be underreported. To the extent that individuals underreport crimes more than arrests, this will also bias arrest rates upward. Unless arrests are substantially underreported compared to actual thefts of greater than $50, these arrest rates should overestimate true arrest probabilities among those choosing to steal.

[12] Arrests and offenses known to the police are taken from the Federal Bureau of Investigation's *Uniform Crime Reports,* while reporting rates to the police are given by the

TABLE 1—ANNUAL SELF-REPORTED CRIME, ARRESTS, AND BELIEFS AMONG MALES IN THE NLSY97

	All	Blacks	Hispanics	Whites
Number of respondents	4,559	1,169	977	2,413
Percent who stole something worth > $50	5.45	6.37	6.31	5.09
Percent who stole a vehicle	1.20	1.31	1.77	1.06
Avg. number of thefts > $50	0.36	0.44	0.57	0.30
Avg. number of thefts > $50 (of those who stole)	6.69	7.18	9.16	5.99
Percent arrested for any offense	8.37	11.22	9.07	7.61
Percent arrested for theft	1.72	2.28	1.74	1.60
Avg. number of arrests for theft	0.03	0.05	0.03	0.03
Persons arrested for theft/persons who stole > $50	0.32	0.36	0.28	0.31
Persons arrested for theft/persons who stole a vehicle	1.43	1.74	0.98	1.51
Arrests for theft/number of thefts > $50	0.09	0.12	0.06	0.09
Average perceived probability (in percent) of arrest for auto theft:				
A) All individuals	60.53	51.79	53.67	63.74
	(0.48)	(1.00)	(1.04)	(0.59)
B) Individuals who reported stealing something worth more than $50	50.46	43.49	43.61	53.88
	(1.67)	(3.57)	(2.81)	(2.22)
C) Individuals who reported stealing a car	44.78	40.50	39.72	47.42
	(2.97)	(5.82)	(4.65)	(4.16)
D) Weighted by number of thefts worth more than $50	39.31	35.76	35.77	41.71
	(3.02)	(6.50)	(5.96)	(4.09)

Notes: Panel weights used in calculating all statistics. Standard errors for perceived probabilities, corrected for clustering across years for each individual, are in parentheses.

Young males from all racial and ethnic backgrounds tend to report a relatively high perceived probability of arrest (see the bottom half of Table 1). While most previous research has shown that official arrest rates do not vary across races (Michael Tonry 1995), popular discussion often suggests that minorities believe they are more likely to face arrest and serious punishment. This does not appear to be the case here. Both young black (52 percent) and Hispanic (54 percent) males tend to hold significantly *lower* perceived probabilities of arrest for auto theft than the average young white male (64 percent). Conditioning on criminal involvement reduces the racial differences, but does not eliminate the white-minority gap.

The fact that perceived probabilities of arrest are substantially higher than true arrest rates does not necessarily imply that individuals overestimate their own probability of arrest. As noted earlier, individuals who engage in crime may face substantially lower arrest probabilities than those who do not. While this can explain some of the gap between perceptions and actual arrest rates, it is not the entire story. The final row of Table 1 accounts for the possibility that individuals who commit the most crime also hold the lowest perceived probabilities of arrest. If each individual's perceived probability is correct, the weighted average of all perceived probabilities for arrest in the final row should equal the sample arrest rate. As expected, teenage males who are more involved in crime tend to predict better chances of evading arrest. As discussed in Section I, this may be due to optimism among criminals who have been lucky in the past or to heterogeneity in true arrest probabilities and self-selection. Given the fact that criminals are likely to be optimistic, it is surprising that those engaged in auto theft still report such high perceived arrest probabilities (40–47 percent).

An obvious potential explanation for the discrepancy in beliefs and true arrest rates is that individuals misinterpret the question.[13] Rather

Bureau of U.S. Department of Justice, *Criminal Victimization in the United States.*

[13] Examining responses to a variety of questions about the probability of different events occurring in the near

TABLE 2—OLS ESTIMATES OF PERCEIVED PROBABILITY OF ARREST FOR AUTO THEFT (MALES IN NLSY97)
(*In percent*)

Variable	(1)	(2)	(3)	(4)
County arrest rate for motor vehicle theft	0.130	0.076	0.034	0.054
	(0.038)	(0.038)	(0.039)	(0.049)
Age		−0.602	−0.634	−0.293
		(0.338)	(0.337)	(0.566)
Black		−11.671	−11.625	−7.821
		(1.200)	(1.200)	(1.829)
Hispanic		−9.600	−9.100	−8.713
		(1.239)	(1.250)	(1.799)
Living in MSA			−4.699	−3.635
			(1.266)	(1.625)
Family income less than $10,000				2.430
				(2.267)
Living with both natural parents in 1997				0.278
				(1.373)
PIAT score (percentile)				0.120
				(0.021)
Mother a teenager at birth				−1.620
				(2.137)
R-square	0.002	0.019	0.020	0.030
Number of observations	13,800	13,800	13,800	7,141

Notes: All specifications are weighted by panel weights and include a constant. Specifications (2)–(4) also control for year dummies. Standard errors, corrected for clustering across years for each individual, are in parentheses.

than reporting an arrest rate, individuals may respond by reporting the probability that someone who engages in auto theft (perhaps repeatedly) will ever be arrested for that crime. Indeed, this measure of an "arrest rate" (dividing the total number of individuals arrested for theft by the number of individuals stealing something worth more than $50) is much higher (32 percent for the entire sample), as seen in Table 1. Alternatively, individuals may report the probability of arrest for stealing a representative (or random) car, while they choose to steal only cars that offer a substantially lower probability of arrest. It is impossible to know for sure how people interpret and answer these questions. To the extent that these measures of beliefs change in response to new information and affect behavior in economically interesting ways, it is likely that they contain important (if noisy) information about true beliefs. Ultimately, this is an empirical question, which we explore in detail below.

Table 2 uses ordinary least squares (OLS) regression to examine the importance of county-level arrest rates, individual characteristics, family background, and geographic variables in explaining the perceived probability of arrest for auto theft. While the reported results are based on the entire sample of NLSY97 respondents, the results are very similar when restricted to those reporting a theft of something worth more than $50 some time in the previous year. Column 1 examines the relationship between county arrest rates (arrests per crime committed) for motor vehicle theft[14] and the perceived probability of arrest. The estimates suggest a positive correlation with a coefficient of 0.13. Column 2 adds demographic indicators for age and race, while column 3 also adds an indicator for current residence in a Metropolitan Statistical Area (MSA). The coefficient on local

future, James Walker (2001) finds little evidence that NLSY97 youth are unable to grasp the concept of probability.

[14] County arrest rates are computed from the ratio of arrests per person divided by crimes per person in each county from the following sources: U.S. Department of Justice, Federal Bureau of Investigation; UNIFORM CRIME REPORTING PROGRAM DATA [UNITED STATES]: COUNTY-LEVEL DETAILED ARREST AND OFFENSE DATA, 1997–2000 [Computer file]; Inter-university Consortium for Political and Social Research, Ann Arbor, MI.

arrest rates drops substantially in columns 2 and 3, suggesting that much of the correlation between beliefs and official arrest rates is due to locational differences in demographics and population size that are correlated with beliefs. Young males living in an MSA believe they are less likely to be arrested, consistent with lower official arrest rates in urban communities. To the extent that most of the true variation in arrest rates across communities depends on metropolitan status and the demographic characteristics of a neighborhood, it is not surprising that the correlation between beliefs and official county arrest rates, which are undoubtedly measured with error, disappears after controlling for these factors.[15]

Column 4 of Table 2 adds detailed family background measures and math achievement test scores.[16] This has little effect on the estimates already discussed. Young black and Hispanic males report a lower probability of arrest than white males, even after controlling for age, local arrest rates, residence in an MSA, and other family background measures. However, racial differences are smaller than their unconditional counterparts shown in Table 1. Family background has little affect on reported beliefs about the probability of arrest. Other than race/ethnicity, only the effects of Peabody Individual Achievement Test (PIAT) scores for math are statistically significant. In contrast to an "ability to evade" arrest hypothesis, a 10-percentage-point higher math PIAT score implies a 1.2-percentage-point higher perceived chance of arrest.

The considerable variation in beliefs is not well explained by these rich individual and family characteristics—the R^2 statistics for these regressions are no greater than 0.03. Yet, perceptions are fairly stable over time for most respondents. More than 25 percent of respondents do not change their beliefs about the probability of arrest between any 2 years, and 52 percent change their perceived probability by 20 percent or less. The correlation in perceptions between years is roughly 0.32.

B. *Crime and Beliefs in the NYS*

The NYS contains a random sample of 1,725 individuals (918 males) age 11 to 17 in 1976. Respondents were surveyed annually from 1976 to 1980, then again in 1983 and 1986. This paper focuses on the perceptions and criminal behavior of men as reported in the 1983 and 1986 surveys (earlier surveys do not contain information about perceptions of the criminal justice system).[17] Data regarding family background and some neighborhood characteristics are available.

Since most respondents are in their early twenties during the relevant sample period, criminal participation is much lower than in the younger NLSY97 sample. Over the three-year period 1984–1986, 18 percent report stealing something worth less than \$5, and 9 percent report physically attacking someone. Fewer than 4 percent report stealing something worth more than \$50 or breaking into a building or vehicle. Nearly 12 percent report an arrest over the three-year span, although many of those arrests are for minor crimes. Only 1.9 percent are arrested for a property or violent crime.[18]

Dividing the number of arrests for property crimes by the total number of reported break-ins

[15] One might expect that older individuals are better informed about the true arrest rate than are younger respondents. However, the results from including interactions between MSA status and age, as well as county arrest rates and age, do not support this conclusion. Coefficient estimates for these interactions are always insignificantly different from zero.

[16] PIAT scores for math are observed only for individuals with fewer than ten years of schooling. To maintain the representativeness of the sample, all individuals age 16 in 1997 are dropped from regressions including PIAT scores, making the sample representative of males ages 12 to 15 in 1997. The large decline in sample size associated with specification (4) is primarily due to the inclusion of PIAT scores and family income, both of which are missing for a sizeable fraction of the sample.

[17] Surveys for 1983 and 1986 actually took place early in 1984 and 1987, respectively. Perception questions, therefore, refer to beliefs at the beginning of 1984 and 1987. Criminal participation (and most other) questions explicitly ask about the calendar years 1983 and 1986, however. Additionally, the survey taken in early 1987 also asked retrospective questions about criminal participation in 1984 and 1985. In many cases, categorical measures rather than the actual number of crimes committed in a year are reported (especially for 1984 and 1985). In these cases, the number of crimes committed was imputed from the average number of crimes committed among those in that category who reported the actual number of crimes (based on all survey years).

[18] Arrests for property crimes include various forms of theft, evading payment, burglary, breaking and entering, and dealing in stolen goods. Arrests for violent crimes include assault, robbery, and harassment. Other arrests include crimes such as prostitution, vagrancy, and panhandling.

TABLE 3—AVERAGE PERCEIVED PROBABILITIES OF ARREST (MALES IN NYS, 1983 AND 1986)
(*In percent*)

Crime	Blacks	Hispanics	Whites	All	Did not commit this type of crime	Committed this type of crime	Weighted by number of crimes committed
(1) Steal something worth							
$5 or less	43.55	38.37	31.86	33.84	35.64	19.19	20.43
(standard error)	(2.54)	(4.60)	(0.97)	(0.90)	(0.97)	(1.72)	(4.97)
[sample size]	[245]	[46]	[1,151]	[1,468]	[1,307]	[161]	[161]
(2) Steal something worth							
more than $50	63.10	58.57	56.78	57.81	57.94	53.00	46.55
(standard error)	(2.25)	(4.49)	(0.97)	(0.87)	(0.88)	(5.08)	(8.86)
[sample size]	[245]	[46]	[1,151]	[1,468]	[1,428]	[40]	[40]
(3) Break into a building							
or vehicle	67.22	66.33	61.54	62.49	62.77	51.67	44.67
(standard error)	(2.26)	(4.71)	(0.98)	(0.88)	(0.89)	(6.12)	(16.12)
[sample size]	[245]	[46]	[1,151]	[1,468]	[1,432]	[36]	[36]
(4) Attack someone to							
hurt or kill them	72.12	70.61	72.08	72.00	73.43	54.78	52.76
(standard error)	(2.18)	(5.58)	(0.90)	(0.82)	(0.81)	(3.34)	(4.05)
[sample size]	[245]	[46]	[1,151]	[1,468]	[1,355]	[113]	[113]

Note: Standard errors are corrected for clustering across years for each individual.

and thefts greater than $50 produces a property crime arrest rate of slightly less than 5 percent. A similar violent crime arrest rate is produced when dividing the number of arrests for violent crime by the reported number of times individuals used force to obtain something or attacked someone. These arrest rates are less than corresponding official arrest rates in the US population adjusted for nonreporting to the police, especially for violent crimes. (For example, 1986 arrest rates for larceny-theft were 5.5 percent, burglary, 7.4 percent, and assault, 20.4 percent.) However, both the number of crimes and number of arrests in this sample are quite small. Furthermore, the denominators are likely to be inflated due to duplication in reporting of crimes (e.g., some break-ins may also be reported as thefts by respondents).

Individuals were asked to report the probability (in increments of 0.1) that they would be arrested if they were to commit various crimes.[19] Table 3 reports average perceived probabilities of arrest in the NYS for the four crimes studied here: stealing something worth $5 or less, stealing something worth more than $50, breaking into a building or vehicle, and attacking someone to hurt or kill them. As with teenage boys in the NLSY97, perceived arrest rates are higher than official arrest rates in the United States. But, the ranking of crimes by perceived arrest probability, from most to least likely, corresponds to the ranking of actual arrest rates across crime types. Interestingly, black and Hispanic men in the NYS report higher perceived arrest probabilities for property crimes than do white men, in sharp contrast to the NLSY97 findings. However, the differences by race are small for all but petty theft.[20]

The final three columns of Table 3 show how perceptions vary across criminals and noncriminals. The last column weights perceived probabilities by the number of times an individual

[19] Specifically, the survey asks the following questions: "Suppose YOU were to [steal something worth $5 or less, steal something worth more than $50, break into a building or vehicle to steal something or just to look around, attack someone with the idea of seriously hurting or killing him/her]. What are the chances you would be ticketed/arrested?"

[20] Unfortunately, it is impossible to determine whether differences across the NYS and NLSY97 sample are due to differences in time period (mid-1980s versus late 1990s), differences in the types of crimes studied, or differences in respondents' age (early to mid-teens versus mid-twenties). Racial differences in beliefs do not appear to differ dramatically by age, suggesting that the latter reason may not be too important.

TABLE 4—OLS ESTIMATES OF PERCEIVED PROBABILITY OF ARREST AMONG MALES IN NYS
(*In percent*)

Variable	(1) Steal something worth < $5	(2) Steal something worth > $50	(3) Break into building or vehicle	(4) Attack someone
Age	−0.596	−1.111	−0.430	0.393
	(0.343)	(0.340)	(0.344)	(0.350)
Black	9.866	4.974	4.958	−0.721
	(3.559)	(3.257)	(3.260)	(3.189)
Hispanic	5.054	1.344	4.964	−0.042
	(5.596)	(5.362)	(5.267)	(5.668)
Rural	4.625	6.866	5.129	3.121
	(2.163)	(2.083)	(2.208)	(2.129)
Central city	−1.813	−1.108	0.584	0.952
	(2.161)	(2.108)	(2.097)	(1.937)
Living with both parents in 1976	−1.545	−0.807	−5.109	−1.053
	(2.387)	(2.353)	(2.333)	(2.216)
Family income < $10,000 in 1976	2.982	0.383	−1.278	−2.039
	(2.606)	(2.490)	(2.592)	(2.442)
Mother graduate from HS	−4.323	−1.189	−2.032	−0.819
	(2.354)	(2.237)	(2.225)	(2.057)
Father graduate from HS	−1.338	−2.554	−3.822	−0.862
	(2.364)	(2.258)	(2.426)	(2.247)
Neighborhood crime a problem	−1.477	0.845	0.354	−2.472
	(1.867)	(1.799)	(1.777)	(1.745)
Neighborhood disarray a problem	0.453	0.212	−1.737	1.444
	(2.223)	(2.162)	(2.181)	(2.107)
R-square	0.039	0.031	0.025	0.006

Notes: All specifications also include an intercept term. Standard errors, corrected for clustering across years for each individual, are in parentheses. Sample size is 1,272.

reported committing that type of crime. As with the teenage boys in the NLSY97, those committing any particular crime tend to believe their chance of arrest for that crime is lower than those not engaging in that type of crime. Weighting beliefs by the number of crimes lowers perceived probabilities even more for all crimes except petty theft. Regardless of the sample, perceived probabilities of arrest are high compared to average arrest rates in the United States.

The effects of age, race, family background, neighborhood conditions, and urban status on perceptions among young men are estimated using OLS and reported in Table 4. (Ordered probits yield similar conclusions.) Even after controlling for other background characteristics, blacks hold a significantly higher perceived probability of arrest than whites for petty theft, but not for other crimes. Men who grew up in intact families and have more educated mothers or fathers think that their likelihood of arrest is lower on average, although the differences are quite small and generally statistically insignificant. Consistent with official arrest patterns, men in rural areas hold higher perceived probabilities of arrest than those in urban communities.[21] The broken windows theory of Kelling and Wilson (1982) assumes that local neighborhood conditions affect individual perceptions about the likelihood of arrest and/or punishment and that those perceptions, in part, determine criminal behavior. The small and insignificant coefficients on neighborhood crime and disarray fail to support this theory.

As in the NLSY97, the substantial differences in beliefs are stable but not well explained by background and neighborhood characteristics. For each crime, approximately 20 percent of young men in the NYS do not change their perceived probability of arrest, while about 60

[21] State and county of residence are unknown in the NYS, so perceptions cannot be compared with local official arrest rates as in the NLSY97.

percent change their perceived probability by 20 percent or less over a three-year period.

III. Information-Based Belief Updating

This section empirically studies factors that may cause individuals to change their beliefs about the probability of arrest. In the NLSY97 and NYS, we assume the reported measure of the perceived probability of arrest, $p_{i,t}$, relates to $E(\pi|H_i^t)$ as defined in Section I. A simple Bayesian updating model suggests estimating the relationship between changes in perceptions and changes in environmental factors $Z_{i,t}$ (e.g., local arrest rates, metropolitan status, neighborhood characteristics), new arrests $A_{i,t}$, and crimes committed $c_{i,t}$ (both taking place between period $t - 1$ and t) by the respondent and by his siblings, $\tilde{A}_{i,t}$ and $\tilde{c}_{i,t}$:

$$\Delta p_{i,t} = \Delta Z_{i,t}\gamma + \phi A_{i,t} + \lambda c_{i,t} + \phi_s \tilde{A}_{i,t} + \lambda_s \tilde{c}_{i,t} + u_{i,t}. \tag{1}$$

A more general structure of updating can also be estimated as follows:

$$p_{i,t} = Z_{i,t}\gamma + \theta p_{i,t-1} + \phi A_{i,t} + \lambda c_{i,t} + \phi_s \tilde{A}_{i,t} + \lambda_s \tilde{c}_{i,t} + \varepsilon_{i,t}, \tag{2}$$

which relaxes the implicit assumption of the Bayesian model that $\theta = 1$. In this case, some $Z_{i,t}$ variables (e.g., ability, race, family background) may be time-invariant. While these variables are differenced out in equation (1), they can play an important role in this more general updating equation. With $|\theta| < 1$ and $Z_{i,t} = Z_i^*$ constant, beliefs would eventually converge to a steady state,

$$p_i^*(Z_i^*) = Z_i^* \frac{\gamma}{1-\theta}, \tag{3}$$

if the individual and his siblings stopped committing crime and were never arrested again (ignoring changes in $\varepsilon_{i,t}$). Consequently, an individual's permanent Z_i characteristics determine his "baseline" level of beliefs. Changes in time-varying $Z_{i,t}$ factors will affect long-run beliefs, perhaps through information gathered from others or from observing changes in local conditions. For example, moving to a new city may cause an individual to change his beliefs about the probability of arrest, even if he does not engage in crime or face an arrest.

The parameter θ determines the rate at which beliefs move toward their baseline level. A value of θ near zero implies that beliefs quickly converge to their steady-state level given any new information, and that any factors affecting beliefs (e.g., an arrest or nonarrest) have short-lived effects. This would be the case if individuals continually receive strong signals (unobserved by the econometrician) that their probability of arrest is p_i^*. Or, it may simply imply that individuals have short memories and quickly return to some baseline belief about their own probability of arrest.

Let T represent the final period of observation in the data. With at least three periods of data (i.e., $T \geq 3$), we can allow for unobserved individual fixed effects: $\varepsilon_{i,t} = \mu_i + \nu_{i,t}$, assuming that

$$E(\nu_{i,t}|p_i^{t-1}, Z_i^T, A_i^t, c_i^t, \tilde{A}_i^t, \tilde{c}_i^t) = 0 \quad \forall\, t = 2, \dots, T, \tag{4}$$

where $x_i^t = (x_{i1}, x_{i2}, \dots, x_{it})$ represents the entire history through period t for any variable x. This assumes that only Z variables are "strictly exogenous," while all other regressors are "predetermined." By conditioning on c_i^t and A_i^t (rather than c_i^T and A_i^T as with traditional fixed or random effects strategies) in equation (4), we explicitly allow for the fact that $c_{i,t+1}$ and $A_{i,t+1}$ (as well as all future values of crime and arrests) may depend on the current shock $\nu_{i,t}$.[22] This is important, because we expect that subsequent crime depends on current beliefs about the probability of arrest—an issue we examine more closely in the following section.

For $\Delta\nu_{i,t} = \Delta p_{i,t} - [\theta\Delta p_{i,t-1} + \Delta Z_{i,t}\gamma + \phi\Delta A_{i,t} + \lambda\Delta c_{i,t} + \phi_s\Delta\tilde{A}_{i,t} + \Delta\lambda_s\tilde{c}_{i,t}]$, we estimate the general model with fixed effects using GMM and the following moment conditions: $E[p_{i,t-2}\Delta\nu_{i,t}] = 0$, $E[\Delta Z_{i,t}\Delta\nu_{i,t}] = 0$, $E[A_{i,t-1}\Delta\nu_{i,t}] = 0$, $E[\tilde{A}_{i,t-1}\Delta\nu_{i,t}] = 0$, $E[c_{i,t-1}\Delta\nu_{i,t}] = 0$, and

[22] Sibling crimes and arrests are treated in the same way as own crime and arrests.

TABLE 5—BELIEF UPDATING AMONG MALES IN THE NLSY97
(*Dependent variable: Perceived probability of arrest* (*in percent*))

	(A) OLS (First differences)		(B) OLS (Quasi-first differences)		(C) GMM (Quasi-first differences with fixed effects)	
Variable	(1)	(2)	(1)	(2)	(1)	(2)
County arrest rate (in percentage terms)	−0.036	−0.034	0.029	0.030	−0.058	−0.058
	(0.047)	(0.047)	(0.040)	(0.040)	(0.064)	(0.064)
Perceived probability of arrest in previous year (in percentage terms)			0.298	0.299	0.038	0.039
			(0.012)	(0.012)	(0.025)	(0.025)
Stole something worth > \$50 in previous year	−4.060		−8.678		−9.303	
	(2.421)		(2.289)		(3.584)	
Sold drugs in previous year	−4.515		−5.853		−6.387	
	(1.779)		(1.756)		(3.402)	
Arrested for theft in previous year	8.712		9.256		10.021	
	(4.106)		(3.876)		(6.338)	
Num. times stole something worth > \$50 in previous year		−0.314		−0.361		−0.352
		(0.130)		(0.118)		(0.184)
Num. times sold drugs in previous year		0.015		−0.110		0.016
		(0.044)		(0.043)		(0.094)
Num. times arrested for theft in previous year		2.692		3.555		0.562
		(1.629)		(1.553)		(3.024)
Sibling stole something worth > \$50 in previous year	6.813		2.346		−3.060	
	(4.317)		(4.214)		(5.418)	
Sibling sold drugs in previous year	−7.957		−10.594		−3.914	
	(3.087)		(3.129)		(7.305)	
Sibling arrested for theft in previous year	−3.828		1.696		−13.798	
	(7.226)		(7.994)		(14.318)	
Num. times siblings stole something worth > \$50 in previous year		−0.334		−0.281		0.315
		(0.214)		(0.260)		(0.258)
Num. times siblings sold drugs in previous year		−0.086		−0.174		−0.085
		(0.071)		(0.073)		(0.249)
Num. times sibling was arrested for theft in previous year		−1.105		−0.846		−5.024
		(2.043)		(1.803)		(2.840)
Tests (*P*-value):						
No effect of respondent information	0.003	0.076	0.000	0.000	0.008	0.251
No effect of sibling information	0.051	0.037	0.008	0.028	0.731	0.226
Equal respondent and sibling information	0.118	0.199	0.125	0.261	0.346	0.058

Notes: First difference specifications regress changes in beliefs on changes in MSA status and the variables shown in the table. OLS quasi-first difference specifications regress current beliefs on the variables shown in the table as well as controls for race, age, MSA status, year dummies, PIAT percentile, whether the respondent lived with both natural parents at age 14, and whether the respondent's mother was a teenager when he was born. GMM (quasi-first difference with fixed effects) specifications control for age and MSA status in addition to the variables in the table. Tests of no effect of respondent (or sibling) information jointly test whether all coefficients on own (or sibling) crimes and arrests are zero. Test of equal respondent and sibling information tests whether all coefficients on crimes and arrests are equal for siblings and respondents. Tests in panels (A) and (B) are *F*-tests, while those in panel (C) are Wald tests. Sample weights are used. Standard errors for coefficient estimates are in parentheses.

$E[\tilde{c}_{i,t-1}\Delta\nu_{i,t}] = 0$. These moment restrictions are applied for $t = 1999, 2000$ in the NLSY97. This method cannot be used with the NYS data, since only two periods of perceptions data are reported.

Table 5 reports estimates of belief updating in the NLSY97 for the following: (a) OLS regression for the difference equation (1); (b) OLS regression for the quasi-difference equation (2); and (c) GMM for the quasi-difference equation (2) accounting for individual fixed effects. Each panel reports two specifications. The first includes indicators for whether the individual or his male siblings committed crime or were arrested for theft between survey dates. The second includes measures of the actual number of times individuals and their siblings committed crimes and were arrested.[23] Measures based on sibling crimes and arrests refer to male siblings who are also in the main NLSY97 sample. As a result, their ages are always within a few years of the respondent.[24] In general, all specifications show strong evidence of belief updating in response to the respondent's own criminal history. Individuals who reported stealing something worth more than $50 or selling drugs were likely to report a lower perceived probability of arrest (conditional on prior beliefs and the arrest outcome) in the next survey year. The effect of at least one of these crimes is statistically significant at the 10-percent level (most at the 5-percent level) in every specification. Those arrested for a theft increased their perceived probability of arrest (significantly so in most specifications). As shown at the bottom of Table 5, joint tests for whether the coefficients on all individual crime and arrest variables equal zero are rejected for all but the final specification.

The effects of sibling crime and arrests are less precisely estimated, given that only 27 percent of the respondents have at least one sibling who is also in the NLSY97 sample. Still, a number of coefficient estimates on measures of sibling crime are statistically significant and negative, as expected. The estimated effects of a sibling's arrest are generally not significantly different from zero and are often of the wrong sign. Joint tests for whether the sibling crime and arrest coefficients equal zero are rejected (at the 10-percent level) in all but the last two specifications. Alternatively, joint tests for whether the coefficients on sibling crimes and arrests equal the corresponding coefficients on respondent crime and arrests cannot be rejected for any but the final specification.

The most noticeable difference between the OLS and GMM estimates of equation (2) is the change in the estimated coefficient on lagged beliefs. After controlling for unobserved individual fixed effects, the autocorrelation of the perceived probability of arrest (θ) drops from 0.3 to below 0.04, which implies that there is little persistence in the effects of new information on reported beliefs. Instead, unobserved differences in baseline beliefs appear to explain why some individuals hold a high perceived probability of arrest year after year, while others believe the probability of arrest is much lower.

A more limited analysis is performed using young men in the NYS. Because the NYS records beliefs for only two periods, we cannot estimate the quasi-difference model with fixed effects. We are also unable to analyze the effects of sibling crime and arrests with these data. In Table 6, we report estimates of equation (2) using 1983 and 1986 measures of beliefs, accounting for crimes and arrests that take place between the two surveys (estimates of the first-difference specification are quite similar).[25] Again, we employ two specifications for each type of crime studied. The first includes an indicator variable for whether the individual committed the crime under study (e.g., in column 1, the indicator is one if the individual reported stealing something worth less than $5 and zero otherwise) or was arrested for a violent or property crime during the 1984–1986 period. The second includes measures of the number of crimes committed and arrests over that period.

As in the NLSY97, these men report lower perceived probabilities of arrest for all crime categories at the end of 1986 if they engaged in that type of crime from 1984 to 1986 (three of the four estimates are statistically significant). Coefficients on arrest are always positive and quantitatively large, but they are significantly different from zero only for break-ins. Joint tests of whether the coefficients on crime and arrests are zero are rejected in nearly all of the columns. While the model above suggests that the net effect of a crime and

[23] Ideally, we would use measures for the crime of auto theft and arrests for auto theft in our updating specifications, but auto thefts are rarely observed in the NLSY97 data and arrests for auto theft cannot be identified. Assuming beliefs about the probability of arrest are positively correlated across crimes—in the NYS, correlations in beliefs about the probability of arrest across crimes range from a low of 0.33 between attack and minor thefts to a high of 0.69 between minor and major thefts—we should expect beliefs about the probability of arrest for auto theft to change in response to other crimes and arrests.

[24] Though not reported, specifications controlling for the number of siblings present in the household show nearly identical results—there is little effect of household size on beliefs. Also, estimates are qualitatively similar when using a restricted sample of individuals who reported a theft of greater than $50 in at least one of the previous two years.

[25] Specifications also control for age, race/ethnicity, whether the individual's parents earned less than $10,000 in 1976, and whether the individual lived with both natural parents in 1976.

TABLE 6—BELIEF UPDATING AMONG MALES IN THE NYS
(*Dependent variable: Perceived probability of arrest* (*in percent*) *in 1986*)

	Steal something worth < $5		Steal something worth > $50		Break in		Attack someone	
Variable	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Perceived probability of arrest in 1983 (in percentage terms)	0.318 (0.037)	0.319 (0.047)	0.329 (0.036)	0.325 (0.036)	0.371 (0.037)	0.370 (0.036)	0.249 (0.036)	0.268 (0.036)
Committed respective crime since 1984	−12.387 (3.283)		−8.669 (5.678)		−25.639 (7.024)		−19.164 (3.591)	
Number of times committed respective crime since 1984		−0.318 (0.139)		−0.870 (0.392)		−4.283 (1.708)		−4.642 (0.863)
Arrested for violent or property crime since 1984	6.568 (8.167)		7.103 (8.136)		18.097 (7.980)		12.012 (7.672)	
Number of times arrested for violent or property crime since 1984		4.300 (6.415)		10.008 (6.729)		15.297 (6.681)		9.349 (6.245)
Central city status	1.528 (2.536)	−1.772 (3.074)	0.946 (2.450)	0.751 (2.452)	2.740 (2.439)	2.522 (2.449)	1.094 (2.404)	1.196 (2.405)
Rural status	0.945 (3.056)	0.192 (4.031)	3.480 (2.944)	3.173 (2.946)	3.446 (2.931)	3.488 (2.943)	−0.150 (2.903)	−0.059 (2.904)
Neighborhood crime a problem	−1.085 (2.431)	−0.650 (3.004)	1.647 (2.360)	0.915 (2.353)	2.789 (2.347)	1.720 (2.349)	−1.977 (2.324)	−2.475 (2.317)
Neighborhood disarray a problem	1.345 (2.777)	6.053 (3.543)	−1.647 (2.691)	−1.111 (2.702)	−2.793 (2.676)	−2.297 (2.701)	−0.734 (2.642)	0.195 (2.647)
Victim of a crime since 1984	1.878 (2.322)	−4.332 (2.855)	3.698 (2.249)	3.605 (2.243)	2.618 (2.228)	2.761 (2.240)	1.788 (2.205)	1.589 (2.208)
Tests (*P*-value):								
No effect of respondent information	0.001	0.068	0.288	0.066	0.001	0.014	<.0001	<.0001
No effect of neighborhood crime or disarray	0.852	0.217	0.725	0.889	0.396	0.628	0.573	0.536

Notes: All specifications also control for age, race/ethnicity (black and Hispanic), whether the individual's parents earned less than $10,000 in 1976, and whether the individual lived with both natural parents in 1976. Test for no effect of respondent information is an *F*-test for whether the coefficients on arrests and crimes committed since 1984 are both zero. Test for no effect of neighborhood crime or disarray is an *F*-test for whether the coefficients on changes in neighborhood crime and disarray indicators are both zero.

arrest should be negative, the specifications with only an indicator for committing a crime and getting arrested generally reveal a coefficient on the indicator for crime that is larger in absolute value than the coefficient on the arrest indicator. This is because those who are arrested commit more than one crime, on average. The specifications controlling for the number of crimes and arrests suggest that the net effect of a single crime and arrest on the perceived probability of arrest is always positive.

It is interesting to note that using measures for any arrest rather than arrests for more serious property and violent crimes (as in Table 6) generally produces smaller and insignificant effects on beliefs (except for small thefts). This suggests that police attempts to crack down on vagrancy, public intoxication, and other petty crimes are not likely to influence beliefs about the probability of arrest for more serious crimes in any significant way.

Table 6 also reports coefficient estimates on central city status and rural residential status. The effects of these measures are insignificant once we control for crime and arrest histories and previous measures of beliefs (in contrast to those in Table 4). Measures of neighborhood lawlessness and disarray also have no significant effect on beliefs. Again, we find no evidence to support the broken windows theory of Wilson and Kelling (1982).

If all individuals face identical probabilities of arrest, information acquired as a victim should be as useful as information acquired as a perpetrator (assuming victims observe whether or not a perpetrator is arrested). In the NYS, it is possible to explore this issue since respondents report whether they were victimized between surveys. Unfortunately, the data do not record whether the perpetrator was arrested, but it is reasonable to assume that no arrest was made in most cases, given such low official arrest rates. In this case, individuals should, on average, adjust their perceived probability of arrest downward after a victimization.[26] The estimated coefficients on victimization in Table 6 are small and statistically insignificant for all crimes, suggesting that individuals put little weight on the information provided by the arrest outcomes of random criminals.

IV. The Influence of Perceptions on Criminal Behavior

Given the considerable variation in perceptions about the probability of arrest, it is natural to question whether individuals act differently based on stated beliefs. And, do they behave differently in periods when they report a high perceived probability of arrest from when they report a low probability? Rational choice theory suggests that (holding all else constant), individuals facing a higher probability of arrest and/or punishment should commit less crime. We examine this relationship in both the NLSY97 and NYS using a linear probability model:

$$c_{it} = W_{i,t}A + Bp_{i,t-1} + v_{i,t}, \tag{5}$$

where $W_{i,t}$ represents observed individual characteristics that may affect the costs of, or returns to, crime (e.g., family background, race, age), and $v_{i,t}$ are i.i.d. shocks to current criminal returns/costs. As before, $c_{i,t}$ is an indicator for whether an individual committed a crime between survey dates $t - 1$ and t, and $p_{i,t-1}$ reflects beliefs about the probability of arrest as of survey date $t - 1$. Since we explore the effects of elicited perceptions in the previous survey year on retrospective crime reported in the current survey, we are left with three years of belief-crime data in the NLSY97 and a single cross section in the NYS.

Assuming $v_{i,t}$ shocks are mean independent of both $W_{i,t}$ and beliefs about the probability of arrest (this assumption is relaxed below), equation (5) can be estimated by OLS. Since the NLSY97 data contain the perceived probability of arrest only for auto theft, we use these data to analyze the effects of beliefs on thefts of something worth more than \$50 and on auto theft. In addition to the perceived probability of arrest for auto theft, we control for official county-level arrest rates (measured as arrests per crime), age, race/ethnicity, residence in an MSA, whether the respondent lived with both natural parents in 1997, whether the mother was a teenager when the respondent was born, and PIAT scores. The OLS estimates suggest that the perceived probability of arrest for auto theft significantly reduces both auto theft and serious theft more generally. Based on sample crime rates reported in Table 1, the estimates imply that a 10-percentage-point increase in the perceived probability of arrest would reduce major thefts by nearly 4 percent and auto theft by 7 percent.[27] Official county-level arrest rates are estimated to have no impact on auto theft and a perverse effect on major thefts.

Using the NYS data, we use OLS to estimate the effects of crime-specific beliefs about the probability of arrest (in 1983) on criminal participation over the 1984–1986 period controlling for age, race/ethnicity, whether the respondent lived with both natural parents in 1976, whether parental income was below \$10,000 in 1976, and rural and central city residential status. All estimated coefficients on the crime-specific per-

[26] Of course, if those who observe an arrest adjust their beliefs upward much more than those who do not observe an arrest adjust their beliefs downward, this need not be the case. Given that official arrest rates range from 5 to 20 percent for the crimes under study, those observing an arrest would have to adjust their beliefs upward by 5 to 20 times as much as those not observing an arrest adjust theirs downward for the effects to cancel. This is unlikely, given that the estimated negative coefficients on (own and sibling) crime measures remain significantly negative when leaving out arrest outcomes in updating regressions (i.e., Tables 5 and 6).

[27] Coefficient estimates on $p_{i,t-1}$ for the linear probability model are -0.00021 (standard error of 0.00008) for thefts worth more than \$50 and -0.0008 (standard error of 0.00004) for auto theft. Estimates using a logit or probit specification produce very similar conclusions.

ceived probability of arrest are negative, supporting the case for deterrence. The estimates suggest that a 10-percentage-point increase in the perceived probability of arrest for each of the four observed crime types reduces participation in that crime by 7 to 12 percent. Estimated effects on both minor thefts and attack are statistically significant at the 5-percent level.

These OLS estimates will be biased if perceived arrest probabilities are correlated with general unobserved preferences for risk and crime.[28] With the NLSY97 data, it is possible to incorporate permanent unobserved differences, assuming $v_{i,t} = \xi_i + \eta_{i,t}$.[29] In general, we would expect ξ_i to be correlated with $p_{i,t-1}$, since ξ_i is a determinant of past participation in crime and since past criminal behavior affects current beliefs. By first-differencing equation (5), we can eliminate the unobserved fixed effect. However, $\Delta p_{i,t-1}$ will tend to be correlated with $\Delta\eta_{i,t}$, since $\eta_{i,t-1}$ affects $c_{i,t-1}$, which then affects $p_{i,t-1}$ (i.e., past shocks to criminal costs or returns affect past criminal behavior, which affects current beliefs). Assuming that $\eta_{i,t}$ is independent of W_i^T, p_i^{t-1}, and of all lagged values of crime and arrests for the individual and his siblings, we can use the following instruments for $\Delta p_{i,t-1}$: $p_{i,t-2}$, the number of thefts of something worth more than \$50 by the individual and his siblings reported in survey year $t - 2$, and the number of arrests for theft reported by the individual and his siblings in survey year $t - 2$ (i.e., we assume that beliefs and past criminal and arrest histories are "predetermined" rather than strictly exogenous). Consistent with the estimates presented in Section III, these instruments are quite strong in predicting changes in beliefs. Results from two-stage least squares estimation of the first-differenced crime equation are consistent with the OLS estimates discussed above. A 10-percentage-point increase in the perceived probability of arrest reduces criminal participation in major thefts by about 3 percent and in auto theft by more than 8 percent. The effect on auto theft is statistically significant at the 5-percent level.[30]

Treating these fixed-effect instrumental variable estimates as the deterrent effect of perceived arrest probabilities, it is possible to study the extent to which differences in beliefs are responsible for differences in criminal participation by race or ability. The estimated 7.8-percentage-point difference in perceived arrest probabilities between whites and blacks (Table 2, column 4) implies a 6.8-percent higher participation rate in auto theft by blacks. Hispanics are predicted to have a 7.6-percent higher participation rate in auto theft than whites due to differences in perceived arrest probabilities. The predicted difference in auto theft participation rates between individuals at the seventy-fifth and twenty-fifth percentiles in PIAT math scores is 5.2 percent. These simple comparisons suggest that important variation in criminal participation rates across individuals may be due to differences in information and beliefs.

V. Conclusions

Among young males in the NLSY97 and NYS, we observe substantial heterogeneity in beliefs about the probability of arrest which is largely unexplained by differences in race, family background, neighborhood, or cognitive abilities. Perceived arrest probabilities are substantially lower among those actively engaged in crime, as predicted by deterrence theory and theories of belief updating. Beliefs are weakly correlated with county-level measures of arrest-per-crime rates and metropolitan/urban residential status. But, contrary to the broken windows theory developed by Wilson and Kelling (1982), perceptions are not correlated with other neighborhood

[28] Two sets of results suggest that this may not be an important concern. First, estimates using NLSY97 data (and identical specifications to those above) suggest that the perceived probability of arrest for auto theft has negligible and statistically insignificant effects on minor delinquent activities like smoking and drinking. Second, the estimated effects of beliefs on crime in the NYS remain, even after controlling for whether the respondent's parents or peers would disapprove of them stealing something and whether they themselves believe stealing is wrong.

[29] Because we do not observe crime subsequent to both surveys with perception measures in the NYS, we are unable to address unobserved heterogeneity in these data.

[30] Coefficient estimates on $\Delta p_{i,t-1}$ are -0.00016 (standard error of 0.00012) for thefts worth more than \$50 and -0.00010 (standard error of 0.00005) for auto theft. These are estimated using a stacked regression of changes in crime from 1998 to 1999 and 1999 to 2000 for all individuals. Standard errors are corrected for clustering at the individual level.

conditions like general lawlessness or abandoned buildings. Furthermore, perceptions are not significantly affected by one's own criminal victimization, which might provide additional information about the likelihood of arrest.

While beliefs are largely unresponsive to most outside influences, they do respond to an individual's own experiences with crime and police. Individuals who engage in crime while avoiding arrest tend to reduce their perceived probability of arrest; those who are arrested raise their perceived probability. Beliefs respond similarly to changes in the criminal history of their siblings, but they do not appear to adjust in response to a sibling's arrest. Thus, individuals may share information and learn from other family members, but the evidence on this is mixed.

Finally, there is robust evidence in favor of deterrence theory based on an individual's perceived probability of arrest (and not actual local arrest rates). Estimates suggest that the effects of differences in beliefs about the probability of arrest play an important role in explaining differences in criminal participation by race, ethnicity, or ability.

Altogether, the empirical findings support a simple economic model of belief updating and crime. Beliefs are heterogeneous and idiosyncratic, but individuals adjust their perceived probability of arrest as they interact with the criminal justice system. Consequently, responses to changes in enforcement are likely to differ across individuals, depending on their own criminal and arrest experiences. The full impacts of enforcement policies may not be realized for many years, and policies that intervene to directly affect perceptions about the probability of arrest may effectively deter crime.

REFERENCES

Bachman, Ronet, Raymond Paternoster, and Sally Ward. 1992. "The Rationality of Sexual Offending: Testing a Deterrence/Rational Choice Conception of Sexual Assault." *Law and Society Review*, 26(2): 343–72.

Becker, Gary S. 1968. "Crime and Punishment: An Economic Approach." *Journal of Political Economy*, 76(2): 169–217.

Corman, Hope, Theodore Joyce, and Norman Lovitch. 1987. "Crime, Deterrence and the Business Cycle in New York City: A VAR Approach." *Review of Economics and Statistics*, 69(4): 695–700.

Grogger, Jeffrey. 1991. "Certainty vs. Severity of Punishment." *Economic Inquiry*, 29(2): 297–309.

Horney, Julie, and Ineke Haen Marshall. 1992. "Risk Perceptions among Serious Offenders: The Role of Crime and Punishment." *Criminology*, 30(4): 575–94.

Levitt, Steven D. 1997. "Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime." *American Economic Review*, 87(3): 270–90.

Levitt, Steven D. 1998. "Why Do Increased Arrest Rates Appear to Reduce Crime: Deterrence, Incapacitation, or Measurement Error?" *Economic Inquiry*, 36(3): 353–72.

Lochner, Lance. 2004. "Belief Updating and Criminal Careers." Unpublished.

Minor, W. William, and Joseph Harry. 1982. "Deterrent and Experiential Effects in Perceptual Deterrence Research: A Replication and Extension." *Journal of Research in Crime and Delinquency*, 19(2): 190–203.

Nagin, Daniel. 1993. "Enduring Individual Differences and Rational Choice Theories of Crime." *Law and Society Review*, 27(3): 467–96.

Nagin, Daniel. 1998. "Criminal Deterrence Research at the Outset of the Twenty-First Century." *Crime and Justice*, 23: 1–42.

Paternoster, Raymond, Linda Saltzman, Gordon Waldo, and Theodore Chiricos. 1983. "Estimating Perceptual Stability and Deterrent Effects: The Role of Perceived Punishment in the Inhibition of Criminal Involvement." *Journal of Criminal Law and Criminology*, 74(1): 270–97.

Paternoster, Raymond, Linda Saltzman, Gordon Waldo, and Theodore Chiricos. 1985. "Assessments of Risk and Behavioral Experience: An Exploratory Study of Change." *Criminology*, 23(3): 417–36.

Paternoster, Raymond, and Sally Simpson. 1996. "Sanction Threats and Appeals to Morality: Testing a Rational Choice Model of Corporate Crime." *Law and Society Review*, 30(3): 549–83.

Piliavin, Irving, Rosemary Gartner, Craig Thornton, and Ross Matsueda. 1986. "Crime, Deterrence, and Rational Choice." *American Sociological Review*, 51(1): 101–19.

Pogarsky, Greg, and Alex Piquero. 2003. "Can Punishment Encourage Offending? Investigating the 'Resetting' Effect." *Journal of Research in Crime and Delinquency*, 40(1): 95–120.

Richards, Pamela, and Charles Title. 1981. "Gender and Perceived Chances of Arrest." *Social Forces*, 59(4): 1182–99.

Sah, Raaj K. 1991. "Social Osmosis and Patterns of Crime." *Journal of Political Economy*, 99(6): 1272–95.

Saltzman, Linda, Raymond Paternoster, Gordon Waldo, and Theodore Chiricos. 1982. "Deterrent and Experiential Effects: The Problem of Causal Order in Perceptual Deterrence Research." *Journal of Research in Crime and Delinquency*, 19(2): 172–89.

Tauchen, Helen, Ann Dryden Witte, and Harriet Griesinger. 1994. "Criminal Deterrence: Revisiting the Issue with a Birth Cohort." *Review of Economics and Statistics*, 76(3): 399–412.

Tonry, Michael. 1995. *Malign Neglect—Race, Crime, and Punishment in America*. New York: Oxford University Press.

Waldfogel, Joel. 1993. "Criminal Sentences as Endogenous Taxes: Are They 'Just' or 'Efficient'?" *Journal of Law and Economics*, 36(1): 139–51.

Walker, James R. 2001. "Adolescents' Expectations Regarding Birth Outcomes: A Comparison of the 1979 and 1997 NLS Cohorts." In *Social Awakenings: Adolescents' Behavior as Adulthood Approaches*, ed. Robert T. Michael, 201–29. New York: Russell Sage.

Wilson, James Q., and George L. Kelling. 1982. "The Police and Neighborhood Safety: Broken Windows." *The Atlantic*, 249(3): 29–38.

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1. Peter Maniloff. 2019. Can Learning Explain Deterrence? Evidence from Oil and Gas Production. *Journal of the Association of Environmental and Resource Economists* **6**:5, 853-881. [Crossref]
2. Riley Tucker, Gregory M. Zimmerman, Jacob I. Stowell, David Squier Jones. 2019. Examining the (Dis)Agreement between Etiology and Consequences of Adults' and Youths' Perceptions of Collective Efficacy in Boston. *Journal of Research in Crime and Delinquency* **155**, 002242781985963. [Crossref]
3. Olivia K. Ha, Evan C. McCuish, Martin A. Andresen, Raymond R. Corrado. 2019. Signalling Desistance? Crime Attitudes, Perceptions of Punishment, and Exposure to Criminogenic Models. *Journal of Developmental and Life-Course Criminology* **21**. . [Crossref]
4. Mirko Draca, Theodore Koutmeridis, Stephen Machin. 2019. The Changing Returns to Crime: Do Criminals Respond to Prices?. *The Review of Economic Studies* **86**:3, 1228-1257. [Crossref]
5. Bo L. Terpstra, Ben C. J. van Velthoven, Peter W. van Wijck. 2019. Do Intensified Police Controls Change Perceptions of Apprehension Probability: A Field Experiment. *Crime & Delinquency* **42**, 001112871983335. [Crossref]
6. Helmut Hirtenlehner. 2019. Does Perceived Peer Delinquency Amplify or Mitigate the Deterrent Effect of Perceived Sanction Risk?. *Deviant Behavior* **40**:3, 361-384. [Crossref]
7. Katharina Neissl, Ekaterina V. Botchkovar, Olena Antonaccio, Lorine A. Hughes. 2019. Rational Choice and the Gender Gap in Crime: Establishing the Generality of Rational Choice Theory in Russia and Ukraine. *Justice Quarterly* 1. [Crossref]
8. Robert Dur, Ben Vollaard. 2019. Salience of law enforcement: A field experiment. *Journal of Environmental Economics and Management* **93**, 208-220. [Crossref]
9. Danielle E. Warren, Maurice E. Schweitzer. 2019. When weak sanctioning systems work: Evidence from auto insurance industry fraud investigations. *Organizational Behavior and Human Decision Processes* . [Crossref]
10. Eugen Dimant, Gerben A. van Kleef, Shaul Shalvi. 2019. Requiem for a Nudge: Framing Effects in Nudging Honesty. *SSRN Electronic Journal* . [Crossref]
11. Floris van Veen, Sebastian Sattler. 2018. Modeling Updating of Perceived Detection Risk: The Role of Personal Experience, Peers, Deterrence Policies, and Impulsivity. *Deviant Behavior* **3**, 1-21. [Crossref]
12. Timothy S. Nixon, J. C. Barnes. 2018. Calibrating Student Perceptions of Punishment: a Specific Test of General Deterrence. *American Journal of Criminal Justice* **49**. . [Crossref]
13. Adeline Delavande, Basit Zafar. 2018. University Choice: The Role of Expected Earnings, Non-pecuniary Outcomes and Financial Constraints. *Journal of Political Economy* . [Crossref]
14. Gregory DeAngelo, R Kaj Gittings, Anita Alves Pena. 2018. Interracial face-to-face crimes and the socioeconomics of neighborhoods: Evidence from policing records. *International Review of Law and Economics* **56**, 1-13. [Crossref]
15. Justin T. Pickett. 2018. Using Behavioral Economics to Advance Deterrence Research and Improve Crime Policy: Some Illustrative Experiments. *Crime & Delinquency* **64**:12, 1636-1659. [Crossref]
16. David McKenzie. 2018. Can Business Owners Form Accurate Counterfactuals? Eliciting Treatment and Control Beliefs About Their Outcomes in the Alternative Treatment Status. *Journal of Business & Economic Statistics* **36**:4, 714-722. [Crossref]
17. Nadia Campaniello, Evelina Gavrilova. 2018. Uncovering the gender participation gap in crime. *European Economic Review* **109**, 289-304. [Crossref]
18. Andrew M. Fox, Kenneth J. Novak. 2018. Collaborating to Reduce Violence: The Impact of Focused Deterrence in Kansas City. *Police Quarterly* **21**:3, 283-308. [Crossref]

19. Matteo Tiratelli, Paul Quinton, Ben Bradford. 2018. Does Stop and Search Deter Crime? Evidence From Ten Years of London-wide Data. *The British Journal of Criminology* **58**:5, 1212-1231. [Crossref]
20. Kibrom A. Abay, Goytom Abraha Kahsay. 2018. Long-term effects of alternative deterrence policies: Panel data evidence from traffic punishments in Denmark. *Transportation Research Part A: Policy and Practice* **113**, 1-19. [Crossref]
21. Giovanni Mastrobuoni, David A. Rivers. 2018. Optimising Criminal Behaviour and the Disutility of Prison. *The Economic Journal* **49**. . [Crossref]
22. Moonki Hong, Gary Kleck. 2018. The Short-Term Deterrent Effect of Executions: An Analysis of Daily Homicide Counts. *Crime & Delinquency* **64**:7, 939-970. [Crossref]
23. Levon Barseghyan, Francesca Molinari, Ted O'Donoghue, Joshua C. Teitelbaum. 2018. Estimating Risk Preferences in the Field. *Journal of Economic Literature* **56**:2, 501-564. [Abstract] [View PDF article] [PDF with links]
24. Charles F. Manski. 2018. Survey Measurement of Probabilistic Macroeconomic Expectations: Progress and Promise. *NBER Macroeconomics Annual* **32**:1, 411-471. [Crossref]
25. Charles F. Manski. 2018. More on random utility models with bounded ambiguity. *Theory and Decision* **84**:2, 205-213. [Crossref]
26. Isak Ladegaard. 2018. We Know Where You Are, What You Are Doing and We Will Catch You. *The British Journal of Criminology* **58**:2, 414-433. [Crossref]
27. KYLE J. THOMAS, BENJAMIN C. HAMILTON, THOMAS A. LOUGHRAN. 2018. TESTING THE TRANSITIVITY OF REPORTED RISK PERCEPTIONS: EVIDENCE OF COHERENT ARBITRARINESS. *Criminology* **56**:1, 59-86. [Crossref]
28. JUSTIN T. PICKETT, SEAN PATRICK ROCHE, GREG POGARSKY. 2018. TOWARD A BIFURCATED THEORY OF EMOTIONAL DETERRENCE. *Criminology* **56**:1, 27-58. [Crossref]
29. April A. Johnson, Rebecca LeFebvre. 2018. Contextual Predictors of Protest Behavior on Social Media: A #Ferguson Case Study. *Journal of Information Technology & Politics* **15**:1, 50-65. [Crossref]
30. Claudia M. Landeo, Kathryn E. Spier. 2018. Ordered Leniency: An Experimental Study of Law Enforcement with Self-Reporting. *SSRN Electronic Journal* . [Crossref]
31. Barak Ariel, Matthew Bland, Alex Sutherland. 2017. 'Lowering the threshold of effective deterrence'—Testing the effect of private security agents in public spaces on crime: A randomized controlled trial in a mass transit system. *PLOS ONE* **12**:12, e0187392. [Crossref]
32. Barak Ariel, Henry Partridge. 2017. Predictable Policing: Measuring the Crime Control Benefits of Hotspots Policing at Bus Stops. *Journal of Quantitative Criminology* **33**:4, 809-833. [Crossref]
33. Dimitrios Nikolaou. 2017. Does cyberbullying impact youth suicidal behaviors?. *Journal of Health Economics* **56**, 30-46. [Crossref]
34. Daniel S. Nagin, Cody W. Telep. 2017. Procedural Justice and Legal Compliance. *Annual Review of Law and Social Science* **13**:1, 5-28. [Crossref]
35. Lisa R. Anderson, Gregory DeAngelo, Winand Emons, Beth Freeborn, Hannes Lang. 2017. PENALTY STRUCTURES AND DETERRENCE IN A TWO-STAGE MODEL: EXPERIMENTAL EVIDENCE. *Economic Inquiry* **55**:4, 1833-1867. [Crossref]
36. MiRang Park, Nicholas Perez, Wesley G Jennings, Angela R Gover. 2017. A preliminary examination of the role of deterrence and target hardening on future recidivism risk among burglars in South Korea. *Security Journal* **30**:3, 903-921. [Crossref]
37. Laura Chioda. General and Specific Deterrence 347-390. [Crossref]

38. Johannes Binswanger, Martin Salm. 2017. Does Everyone Use Probabilities? The Role of Cognitive Skills. *European Economic Review* . [Crossref]
39. Daniel Seddig, Helmut Hirtenlehner, Jost Reinecke. 2017. Beeinflussen Sanktionsrisikoeinschätzungen das delinquente Handeln junger Menschen oder ist es umgekehrt?. *KZfSS Kölner Zeitschrift für Soziologie und Sozialpsychologie* **69**:2, 259-282. [Crossref]
40. Adeline Delavande, Jinkook Lee, Seetha Menon. 2017. Eliciting Survival Expectations of the Elderly in Low-Income Countries: Evidence From India. *Demography* **54**:2, 673-699. [Crossref]
41. Xuesong Hu, Xin Wang, Baohua Xin. 2017. Insider Trading: Does Being a Neighbor of the Securities and Exchange Commission Matter?. *Managerial and Decision Economics* **38**:2, 144-165. [Crossref]
42. Aaron Chalfin, Justin McCrary. 2017. Criminal Deterrence: A Review of the Literature. *Journal of Economic Literature* **55**:1, 5-48. [Abstract] [View PDF article] [PDF with links]
43. Frank A. Sloan, Sabrina A. McCutchan, Lindsey M. Eldred. 2017. Alcohol-Impaired Driving and Perceived Risks of Legal Consequences. *Alcoholism: Clinical and Experimental Research* **41**:2, 432-442. [Crossref]
44. GREG POGARSKY, SEAN PATRICK ROCHE, JUSTIN T. PICKETT. 2017. HEURISTICS AND BIASES, RATIONAL CHOICE, AND SANCTION PERCEPTIONS*. *Criminology* **55**:1, 85-111. [Crossref]
45. Nicholas Lovett, Yuhan Xue. 2017. Do Greater Sanctions Deter Youth Crime? Evidence from a Regression Discontinuity Design. *SSRN Electronic Journal* . [Crossref]
46. Frank Sloan, Lindsey Eldred, Sabrina McCutchan, Alyssa Platt. 2016. Deterring Rearrests for Drinking and Driving. *Southern Economic Journal* **83**:2, 416-436. [Crossref]
47. Maria Antonella Mancino, Salvador Navarro, David A. Rivers. 2016. Separating state dependence, experience, and heterogeneity in a model of youth crime and education. *Economics of Education Review* **54**, 274-305. [Crossref]
48. Thomas G. Blomberg. 2016. Police and Crime. *Criminology & Public Policy* **15**:3, 721-725. [Crossref]
49. Anthony A. Braga, Robert Apel. 2016. And We Wonder Why Criminology Is Sometimes Considered Irrelevant in Real-World Policy Conversations. *Criminology & Public Policy* **15**:3, 813-829. [Crossref]
50. Justin T. Pickett, Sean Patrick Roche. 2016. Arrested Development. *Criminology & Public Policy* **15**:3, 727-751. [Crossref]
51. Greg Pogarsky, Thomas A. Loughran. 2016. The Policy-to-Perceptions Link in Deterrence. *Criminology & Public Policy* **15**:3, 777-790. [Crossref]
52. Daniel S. Nagin. 2016. "What We've Got Here Is Failure to Communicate". *Criminology & Public Policy* **15**:3, 753-765. [Crossref]
53. Gary Kleck. 2016. Objective Risks and Individual Perceptions of Those Risks. *Criminology & Public Policy* **15**:3, 767-775. [Crossref]
54. Derek Kreager, Daniel T. Ragan, Holly Nguyen, Jeremy Staff. 2016. When Onset Meets Desistance: Cognitive Transformation and Adolescent Marijuana Experimentation. *Journal of Developmental and Life-Course Criminology* **2**:2, 135-161. [Crossref]
55. Philip A. Curry, Anindya Sen, George Orlov. 2016. Crime, apprehension and clearance rates: Panel data evidence from Canadian provinces. *Canadian Journal of Economics/Revue canadienne d'économique* **49**:2, 481-514. [Crossref]
56. Songman Kang. 2016. Inequality and crime revisited: effects of local inequality and economic segregation on crime. *Journal of Population Economics* **29**:2, 593-626. [Crossref]

57. Fangwen Lu, Jinan Zhang, Jeffrey M. Perloff. 2016. General and specific information in deterring traffic violations: Evidence from a randomized experiment. *Journal of Economic Behavior & Organization* **123**, 97-107. [Crossref]
58. Justin T. Pickett, Thomas A. Loughran, Shawn Bushway. 2016. Consequences of legal risk communication for sanction perception updating and white-collar criminality. *Journal of Experimental Criminology* **12**:1, 75-104. [Crossref]
59. THOMAS A. LOUGHRAN, RAY PATERNOSTER, AARON CHALFIN, THEODORE WILSON. 2016. CAN RATIONAL CHOICE BE CONSIDERED A GENERAL THEORY OF CRIME? EVIDENCE FROM INDIVIDUAL-LEVEL PANEL DATA. *Criminology* **54**:1, 86-112. [Crossref]
60. Adeline Delavande, Hans-Peter Kohler. 2016. HIV/AIDS-related Expectations and Risky Sexual Behaviour in Malawi. *The Review of Economic Studies* **83**:1, 118-164. [Crossref]
61. Luisa Blanco. 2016. The Impact of Judicial Reform on Crime Victimization and Trust in Institutions in Mexico. *Violence and Victims* **31**:1, 27-50. [Crossref]
62. Giovanni Mastrobuoni, David A Rivers. 2016. Criminal Discount Factors and Deterrence. *SSRN Electronic Journal* . [Crossref]
63. Emily Weisburst. 2016. Safety in Police Numbers: Evidence of Police Effectiveness and Foresight from Federal COPS Grant Applications. *SSRN Electronic Journal* . [Crossref]
64. Robert Dur, Ben Vollaard. 2016. Salience of Law Enforcement: A Field Experiment. *SSRN Electronic Journal* . [Crossref]
65. Shannon Ward, Jenny Williams. 2015. Does Juvenile Delinquency Reduce Educational Attainment?. *Journal of Empirical Legal Studies* **12**:4, 716-756. [Crossref]
66. Heiko Rauhut. 2015. Stronger inspection incentives, less crime? Further experimental evidence on inspection games. *Rationality and Society* **27**:4, 414-454. [Crossref]
67. Lamar Pierce, Daniel C. Snow, Andrew McAfee. 2015. Cleaning House: The Impact of Information Technology Monitoring on Employee Theft and Productivity. *Management Science* **61**:10, 2299-2319. [Crossref]
68. Antonio Merlo, Kenneth I. Wolpin. 2015. The transition from school to jail: Youth crime and high school completion among black males. *European Economic Review* **79**, 234-251. [Crossref]
69. Rebeca Bautista, Esther Sitges, Sonia Tirado. 2015. Psychosocial Predictors of Compliance with Speed Limits and Alcohol Limits by Spanish Drivers: Modeling Compliance of Traffic Rules. *Laws* **4**:3, 602-616. [Crossref]
70. Thomas A. Loughran, Ray Paternoster, Douglas B. Weiss. Deterrence 50-74. [Crossref]
71. M. Wiswall, B. Zafar. 2015. Determinants of College Major Choice: Identification using an Information Experiment. *The Review of Economic Studies* **82**:2, 791-824. [Crossref]
72. Frank A. Sloan, Lindsey M. Eldred. 2015. Do preferences of drinker-drivers differ?. *International Journal of Health Economics and Management* . [Crossref]
73. DANIEL S. NAGIN, ROBERT M. SOLOW, CYNTHIA LUM. 2015. DETERRENCE, CRIMINAL OPPORTUNITIES, AND POLICE. *Criminology* **53**:1, 74-100. [Crossref]
74. Brendan O'Flaherty, Rajiv Sethi. Urban Crime 1519-1621. [Crossref]
75. Jesús Soto Pineda. 2015. Propuesta De Aplicación De Los Elementos De Configuración De La Disuasión Al Derecho Del Consumo En Colombia (A Proposition of Application of the Elements of Deterrence to the Consumer Protection Act in Colombia). *SSRN Electronic Journal* . [Crossref]

76. Thomas A. Loughran, Ray Paternoster, Kyle J. Thomas. 2014. Incentivizing Responses to Self-report Questions in Perceptual Deterrence Studies: An Investigation of the Validity of Deterrence Theory Using Bayesian Truth Serum. *Journal of Quantitative Criminology* **30**:4, 677-707. [Crossref]
77. Christopher J. Sullivan, Jean Marie McGloin. 2014. Looking Back to Move Forward. *Journal of Research in Crime and Delinquency* **51**:4, 445-466. [Crossref]
78. Sonja Schulz. 2014. Individual Differences in the Deterrence Process: Which Individuals Learn (Most) from Their Offending Experiences?. *Journal of Quantitative Criminology* **30**:2, 215-236. [Crossref]
79. Brian Bell, Laura Jaitman, Stephen Machin. 2014. Crime Deterrence: Evidence From the London 2011 Riots. *The Economic Journal* **124**:576, 480-506. [Crossref]
80. Yang Wang. 2014. Dynamic Implications of Subjective Expectations: Evidence from Adult Smokers. *American Economic Journal: Applied Economics* **6**:1, 1-37. [Abstract] [View PDF article] [PDF with links]
81. Kari Britt Schroeder, Gillian V. Pepper, Daniel Nettle. 2014. Local norms of cheating and the cultural evolution of crime and punishment: a study of two urban neighborhoods. *PeerJ* **2**, e450. [Crossref]
82. Derek A. Kreager, Ross L. Matsueda. Bayesian Updating and Crime 116-125. [Crossref]
83. Gary Kleck. Deterrence: Actual Versus Perceived Risk of Punishment 1014-1023. [Crossref]
84. Greg Pogarsky. Offender Decision Making and Behavioral Economics 3311-3315. [Crossref]
85. Michael A. Arnold, Eric Darmon, Sylvain Dejean, Thierry PPnard. 2014. Graduated Response Policy and the Behavior of Digital Pirates: Evidence from the French Three-Strike (Hadopi) Law. *SSRN Electronic Journal* . [Crossref]
86. Brendan O'Flaherty, Rajiv Sethi. 2014. Urban Crime. *SSRN Electronic Journal* . [Crossref]
87. Shannon Ward, Jenny Williams. 2014. Does Juvenile Delinquency Reduce Educational Attainment?. *SSRN Electronic Journal* . [Crossref]
88. Adeline Delavande, Basit Zafar. 2014. University Choice: The Role of Expected Earnings, Non-pecuniary Outcomes, and Financial Constraints. *SSRN Electronic Journal* . [Crossref]
89. Johan Blomquist, Joakim Westerlund. 2013. A Non-Stationary Panel Data Investigation of the Unemployment–Crime Relationship. *Social Science Research* . [Crossref]
90. Dietrich Earnhart, Lana Friesen. 2013. Can Punishment Generate Specific Deterrence Without Updating? Analysis of a Stated Choice Scenario. *Environmental and Resource Economics* **56**:3, 379-397. [Crossref]
91. Marco Gonzalez-Navarro. 2013. Deterrence and Geographical Externalities in Auto Theft. *American Economic Journal: Applied Economics* **5**:4, 92-110. [Abstract] [View PDF article] [PDF with links]
92. Gary Kleck, J. C. Barnes. 2013. Deterrence and Macro-Level Perceptions of Punishment Risks. *Crime & Delinquency* **59**:7, 1006-1035. [Crossref]
93. Hunt Allcott. 2013. The Welfare Effects of Misperceived Product Costs: Data and Calibrations from the Automobile Market. *American Economic Journal: Economic Policy* **5**:3, 30-66. [Abstract] [View PDF article] [PDF with links]
94. Christoph Engel, Martin Beckenkamp, Andreas Glöckner, Bernd Irlenbusch, Heike Hennig-Schmidt, Sebastian Kube, Michael Kurschilgen, Alexander Morell, Andreas Nicklisch, Hans-Theo Normann, Emanuel Towfigh. 2013. First Impressions are More Important than Early Intervention Qualifying Broken Windows Theory in the Lab. *International Review of Law and Economics* . [Crossref]
95. Daniel S. Nagin. 2013. Deterrence in the Twenty-First Century. *Crime and Justice* **42**:1, 199-263. [Crossref]

96. Gerlinde Fellner, Rupert Sausgruber, Christian Traxler. 2013. TESTING ENFORCEMENT STRATEGIES IN THE FIELD: THREAT, MORAL APPEAL AND SOCIAL INFORMATION. *Journal of the European Economic Association* **11**:3, 634-660. [Crossref]
97. Christine Horne, Heiko Rauhut. 2013. Using laboratory experiments to study law and crime. *Quality & Quantity* **47**:3, 1639-1655. [Crossref]
98. Robert Apel. 2013. Sanctions, Perceptions, and Crime: Implications for Criminal Deterrence. *Journal of Quantitative Criminology* **29**:1, 67-101. [Crossref]
99. FLORIAN BAUMANN, TIM FRIEHE. 2013. CHEAP TALK ABOUT THE DETECTION PROBABILITY. *International Game Theory Review* **15**:01, 1350003. [Crossref]
100. Frank A. Sloan, Alyssa C. Platt, Lindsey M. Chepke, Claire E. Blevins. 2013. Deterring domestic violence: Do criminal sanctions reduce repeat offenses?. *Journal of Risk and Uncertainty* **46**:1, 51-80. [Crossref]
101. ROBERT DUR, JOËL VAN DER WEELE. 2013. Status-Seeking in Criminal Subcultures and the Double Dividend of Zero-Tolerance. *Journal of Public Economic Theory* **15**:1, 77-93. [Crossref]
102. Daniel S. Nagin. 2013. Deterrence: A Review of the Evidence by a Criminologist for Economists. *Annual Review of Economics* **5**:1, 83-105. [Crossref]
103. Philip A. Curry, Anindya Sen, George Orlov. 2013. Crime, Apprehension and Clearance Rates: Panel Data Evidence from Canadian Provinces. *SSRN Electronic Journal* . [Crossref]
104. Alex R. Piquero, Nicole Leeper Piquero, Marc Gertz, Jake Bratton, Thomas A. Loughran. 2012. Sometimes Ignorance is Bliss: Investigating Citizen Perceptions of the Certainty and Severity of Punishment. *American Journal of Criminal Justice* **37**:4, 630-646. [Crossref]
105. Horst Entorf. 2012. Expected recidivism among young offenders: Comparing specific deterrence under juvenile and adult criminal law. *European Journal of Political Economy* **28**:4, 414-429. [Crossref]
106. Libor Dušek. 2012. Crime, Deterrence, and Democracy. *German Economic Review* **13**:4, 447-469. [Crossref]
107. Todd Stinebrickner, Ralph Stinebrickner. 2012. Learning about Academic Ability and the College Dropout Decision. *Journal of Labor Economics* **30**:4, 707-748. [Crossref]
108. Shelby Gerking, Raman Khaddaria. 2012. PERCEPTIONS OF HEALTH RISK AND SMOKING DECISIONS OF YOUNG PEOPLE. *Health Economics* **21**:7, 865-877. [Crossref]
109. Wilbert van der Klaauw. 2012. On the Use of Expectations Data in Estimating Structural Dynamic Choice Models. *Journal of Labor Economics* **30**:3, 521-554. [Crossref]
110. Qiu Chen, Khim Kelly, Steven E. Salterio. 2012. Do changes in audit actions and attitudes consistent with increased auditor scepticism deter aggressive earnings management? An experimental investigation. *Accounting, Organizations and Society* **37**:2, 95-115. [Crossref]
111. Florian Baumann, Tim Friehe. 2012. Cheap Talk About the Detection Probability. *SSRN Electronic Journal* . [Crossref]
112. Matthew Wiswall, Basit Zafar. 2012. Determinants of College Major Choice: Identification Using an Information Experiment. *SSRN Electronic Journal* . [Crossref]
113. Luisa R. Blanco. 2012. The Impact of Reform on the Criminal Justice System in Mexico. *SSRN Electronic Journal* . [Crossref]
114. Alex R. Piquero, Raymond Paternoster, Greg Pogarsky, Thomas Loughran. 2011. Elaborating the Individual Difference Component in Deterrence Theory. *Annual Review of Law and Social Science* **7**:1, 335-360. [Crossref]
115. THOMAS A. LOUGHRAN, RAYMOND PATERNOSTER, ALEX R. PIQUERO, GREG POGARSKY. 2011. ON AMBIGUITY IN PERCEPTIONS OF RISK:IMPLICATIONS FOR

CRIMINAL DECISION MAKING AND DETERRENCE*. *Criminology* **49**:4, 1029-1061. [Crossref]

116. SHAMENA ANWAR, THOMAS A. LOUGHRAN. 2011. TESTING A BAYESIAN LEARNING THEORY OF DETERRENCE AMONG SERIOUS JUVENILE OFFENDERS*. *Criminology* **49**:3, 667-698. [Crossref]
117. BASIT ZAFAR. 2011. DOUBLE MAJORS: ONE FOR ME, ONE FOR THE PARENTS?. *Economic Inquiry* no-no. [Crossref]
118. Basit Zafar. 2011. Can subjective expectations data be used in choice models? evidence on cognitive biases. *Journal of Applied Econometrics* **26**:3, 520-544. [Crossref]
119. Frank Sloan, Alyssa Platt. 2011. Information, risk perceptions, and smoking choices of youth. *Journal of Risk and Uncertainty* **42**:2, 161-193. [Crossref]
120. Basit Zafar. 2011. How Do College Students Form Expectations?. *Journal of Labor Economics* **29**:2, 301-348. [Crossref]
121. Steven N. Durlauf, Daniel S. Nagin. 2011. Imprisonment and crime. *Criminology & Public Policy* **10**:1, 13-54. [Crossref]
122. Lihui Zhang. 2011. Family, School and Friends: Correlates of Canadian Youth Outcomes. *Child Indicators Research* . [Crossref]
123. Thomas Loughran, Greg Pogarsky, Alex Piquero, Raymond Paternoster. 2011. Re-Examining the Functional Form of the Certainty Effect in Deterrence Theory. *Justice Quarterly* 1-30. [Crossref]
124. Nicolas Marceau, Steeve Mongrain. 2011. Competition in law enforcement and capital allocation. *Journal of Urban Economics* **69**:1, 136-147. [Crossref]
125. Douglas S. Thomas, David T. Butry, Jeffrey P. Prestemon. 2011. Enticing Arsonists with Broken Windows and Social Disorder. *Fire Technology* **47**:1, 255-273. [Crossref]
126. Thomas Loughran, Ray Paternoster, Alex R. Piquero, Jeffrey Fagan. 2011. 'A Good Man Always Knows His Limitations': Overconfidence in Criminal Offending. *SSRN Electronic Journal* . [Crossref]
127. Barton H. Hamilton, Tat Y. Chan, Christopher Makler. 2011. Using Expectations Data to Infer Managerial Preferences. *SSRN Electronic Journal* . [Crossref]
128. Matthew Wiswall, Basit Zafar. 2011. Determinants of College Major Choice: Identification Using an Information Experiment. *SSRN Electronic Journal* . [Crossref]
129. Matthew Wiswall, Basit Zafar. 2011. Determinants of College Major Choice: Identification Using an Information Experiment. *SSRN Electronic Journal* . [Crossref]
130. Charles R. Tittle, Ekaterina V. Botchkovar, Olena Antonaccio. 2010. Criminal Contemplation, National Context, and Deterrence. *Journal of Quantitative Criminology* . [Crossref]
131. Johannes Rincke, Christian Traxler. 2010. Enforcement Spillovers. *Review of Economics and Statistics* 110802123557007. [Crossref]
132. D. Dranove, Y. Watanabe. 2010. Influence and Deterrence: How Obstetricians Respond to Litigation against Themselves and Their Colleagues. *American Law and Economics Review* **12**:1, 69-94. [Crossref]
133. Christine Horne, Heiko Rauhut. 2010. Using Laboratory Experiments to Study Law and Crime. *SSRN Electronic Journal* . [Crossref]
134. Basit Zafar. 2010. Double Majors: One for Me, One for the Parents?. *SSRN Electronic Journal* . [Crossref]
135. Mikko Packalen. 2010. Identification and Estimation of Social Interactions Through Variation in Equilibrium Influence. *SSRN Electronic Journal* . [Crossref]

136. Qiu Chen, Khim Kelly, Steven E. Salterio. 2010. Does Auditing Deter Potentially Fraudulent Earnings Management? An Experimental Investigation. *SSRN Electronic Journal* . [Crossref]
137. Basit Zafar. 2010. Can Subjective Expectations Data be Used in Choice Models? Evidence on Cognitive Biases. *SSRN Electronic Journal* . [Crossref]
138. Ray Paternoster, Greg Pogarsky. 2009. Rational Choice, Agency and Thoughtfully Reflective Decision Making: The Short and Long-Term Consequences of Making Good Choices. *Journal of Quantitative Criminology* **25**:2, 103-127. [Crossref]
139. Robert Apel, Greg Pogarsky, Leigh Bates. 2009. The Sanctions-Perceptions Link in a Model of School-based Deterrence. *Journal of Quantitative Criminology* **25**:2, 201-226. [Crossref]
140. R. Hjalmarsson. 2009. Crime and Expected Punishment: Changes in Perceptions at the Age of Criminal Majority. *American Law and Economics Review* **11**:1, 209-248. [Crossref]
141. Adeline Delavande, Hans-Peter Kohler. 2009. Subjective expectations in the context of HIV/AIDS in Malawi. *Demographic Research* **20**, 817-875. [Crossref]
142. Greg Pogarsky. Deterrence and Decision Making: Research Questions and Theoretical Refinements 241-258. [Crossref]
143. Alessandro Tarozzi, Aprajit Mahajan, Joanne Yoong, Brian Blackburn. 2009. Bednets, Information and Malaria in Orissa. *SSRN Electronic Journal* . [Crossref]
144. Antonio M. Merlo, Kenneth I. Wolpin. 2009. The Transition from School to Jail: Youth Crime and High School Completion Among Black Males, Second Version. *SSRN Electronic Journal* . [Crossref]
145. Johannes Rincke, Christian Traxler. 2009. Deterrence through Word of Mouth. *SSRN Electronic Journal* . [Crossref]
146. Martin Beckenkamp, Christoph Engel, Andreas Glöckner, Bernd Irlenbusch, Heike Hennig-Schmidt, Sebastian Kube, Michael J. Kurschilgen, Alexander Morell, Andreas Nicklisch, Hans-Theo Normann, Emanuel V. Towfigh. 2009. Beware of Broken Windows! First Impressions in Public-Good Experiment. *SSRN Electronic Journal* . [Crossref]
147. Basit Zafar. 2009. How do College Students Form Expectations?. *SSRN Electronic Journal* . [Crossref]
148. Gerlinde Fellner, Rupert Sausgruber, Christian Traxler. 2009. Testing Enforcement Strategies in the Field: Legal Threat, Moral Appeal and Social Information. *SSRN Electronic Journal* . [Crossref]
149. Karen van der Wiel. 2009. Have You Heard the News? How Real-Life Expectations React to Publicity. *SSRN Electronic Journal* . [Crossref]
150. Aprajit Mahajan, Alessandro Tarozzi, Joanne Yoong, Brian Blackburn. 2009. Bednets, Information and Malaria in Orissa. *SSRN Electronic Journal* . [Crossref]
151. Adeline Delavande. 2008. PILL, PATCH, OR SHOT? SUBJECTIVE EXPECTATIONS AND BIRTH CONTROL CHOICE*. *International Economic Review* **49**:3, 999-1042. [Crossref]
152. Michael Tonry. 2008. Learning from the Limitations of Deterrence Research. *Crime and Justice* **37**:1, 279-311. [Crossref]
153. Shawn Bushway, Peter Reuter. 2008. Economists' Contribution to the Study of Crime and the Criminal Justice System. *Crime and Justice* **37**:1, 389-451. [Crossref]
154. Antonio M. Merlo, Kenneth I. Wolpin. 2008. The Transition from School to Jail: Youth Crime and High School Completion among Black Males. *SSRN Electronic Journal* . [Crossref]
155. Andrew R. Gimber. 2007. THE EFFECT OF POLICING STRATEGIES: EVIDENCE FROM THE USA. *Economic Affairs* **27**:4, 17-22. [Crossref]
156. Randi Hjalmarsson. 2007. Crime and Expected Punishment: Changes in Perceptions at the Age of Criminal Majority. *SSRN Electronic Journal* . [Crossref]