A Theoretical and Empirical Study of Individual Perceptions of the Criminal Justice System*

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Abstract

This paper examines perceptions of the criminal justice system held by young males using longitudinal survey data from the recent National Longitudinal Survey of Youth 1997 Cohort and the National Youth Survey. First, a model is developed to study how perceptions respond to individual information about the probability of arrest and how perceptions affect criminal behavior. Then, the model is shown to be consistent with the data. Young males who engage in crime but are not arrested revise their perceived probability of arrest downward, while those who are arrested revise their probability upwards. The perceived probability of arrest is then linked to subsequent criminal behavior – youth with a lower perceived probability of arrest are significantly more likely to engage in crime during subsequent periods. Perceived probabilities of arrest appear to be idiosyncratic and individual-specific. As a result, information about the arrests of others, local neighborhood conditions, and official arrest rates have little impact on the perceptions of any given individual about his own arrest rate.

Another interesting feature of the data on perceptions includes the finding that young males typically report a higher probability of arrest than is actually observed in official arrest rates. Consistent with the model, perceived arrest probabilities among those engaged in crime are lower than those of non-criminals. Despite substantial heterogeneity in the perceived probability of arrest across individuals, those perceptions are difficult to predict from standard background measures, ability, and neighborhood characteristics. Most notably, there do not appear to be substantial differences in perceptions across race and ethnicity for most of the crimes studied.

These findings suggest that heterogeneity in perceptions may be an important cause for differences in criminal participation across individuals. Furthermore, those perceptions can be influenced by the justice system. A model of belief updating and criminal behavior that is consistent with the data suggests that policies enacted to change the actual probability of arrest will have heterogeneous effects on individuals with different crime and arrest histories, but increases in true arrest rates will lower crime. Since it may take time for information about changes in actual arrest rates to disseminate, changes in enforcement policy are likely to have lagged effects on crime rates.

1 Introduction

The economics literature on crime implicitly assumes that individuals are well-informed about arrest rates and, therefore, respond immediately to any changes in the criminal justice system.

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Empirical studies examining deterrence theory have, therefore, focused on actual measures of the police force, arrest rates, or punishment rates rather than measures of individual beliefs.[1] Most have found that increases in the likelihood of arrest or punishment reduce crime.[2]

Conditional on official arrest and incarceration rates, differences in criminal behavior across individuals are typically attributed to differences in tastes for crime, criminal returns, or opportunity costs. Rarely are individual differences in beliefs about the justice system invoked as an explanation for heterogeneous criminal behavior. This is largely because a clear and convincing link between perceptions and criminal behavior has not, yet, been established (e.g. see Piliavian, et al., 1986, or Schneider and Ervin, 1990). Furthermore, extracting useful measures of beliefs from individuals is not an easy task, especially on a topic such as crime. Since few individuals engage in crime to any significant degree, it is likely that few individuals seriously consider the probability of arrest or of facing various punishments associated with crime.

This paper not only establishes an empirical link between the perceived probability of arrest and criminal activity, but it also shows that individuals update their beliefs in rational ways. Individuals reporting a lower perceived probability of arrest are more likely to engage in crime. Those who engage in crime without getting arrested reduce their perceived probability of arrest, while those who are arrested increase their perceived probability.[3]

Understanding the evolution of beliefs is relevant for studies of crime. Sah (1991) provides a theoretical analysis of crime based on a model in which individual beliefs about the probability of punishment are determined by the number of people they observe committing crime and their arrest rates. His theory suggests interesting dynamic responses to changes in criminal enforcement policy as well as levels of segregation. This paper develops a complementary framework for analyzing how an individual's own crime and arrest history affects his beliefs and how those beliefs affect behavior. The model suggests that individuals with similar tastes and initial beliefs may follow different crime paths over their lives if they are arrested at different rates (or even arrested at

[1] Viscusi (1986) is a rare exception. He shows that the required risk premium in criminal earnings is higher for individuals with a higher perceived probability of arrest.

[2] Studies using actual police, arrest, or punishment measures include Blumestein, et al., 1978, Cameron, 1988, Ehrlich, 1973,1981, Grogger, 1991, Levitt, 1997, 1998a, 1998b, Myers, 1983, Tauchen, Witte, and Griesinger, 1994, Trumbull, 1989, Waldfogel, 1993, and Witte, 1980.

[3] Criminologists studying the link between perceptions and crime have reported that individuals engaged in crime tend to lower their perceived probability of arrest, referring to these effects as 'experiential effects' (Minor and Harry, 1982, Paternoster, et al., 1983, Piliavin, et al., 1986, Saltzman, et al., 1982). The main emphasis of these studies has been to point out the flaws inherent in using cross-sectional data on perceptions and criminal behavior to estimate deterrence effects, since the reported behavior is typically prior to the perceptions measure. These studies have not examined the informational issues involved with crime and arrest histories and have ignored the distinction between criminals who become arrested and those who do not – the focus of this paper.

different points in their criminal careers). As with Sah's (1991) framework, there will be delayed responses in criminal activity when official arrest rates increase. As more and more individuals face an arrest, they respond by increasing their perceived probability of arrest and reducing their crime. So, even a temporary increase in the probability of arrest will have long-term impacts on crime rates. The importance of these results depends on the relevance of and information used in belief updating. A primary goal of this paper is to empirically examine the role of individual crime and arrest histories as well as alternative sources of information in determining beliefs about the probability of arrest. The impact of those beliefs on criminal behavior is then examined.

The "broken windows" theory of Wilson and Kelling (1982) suggests that individuals are more likely to engage in crime in neighborhoods exhibiting decay (i.e. broken windows or abandoned buildings), because they believe they are less likely to be arrested or interfered with. Understanding the information used in generating beliefs and how perceptions influence behavior is central to this theory. In the empirical analysis below, we explore the relationship between neighborhood decay and perceptions among young males.

The economics literature has recently begun to analyze how the evolution of beliefs over time can affect aggregate outcomes. In special environments, the information cascade literature (e.g. Banerjee, 1992, Bikhchandani, Hirshleifer, and Welsh, 1992) has shown that the aggregation of individual decisions can lead to informational cascades and conformity when individuals possess idiosyncratic information and gather information from others. More generally, the way in which individuals acquire information and develop expectations is important in determining outcomes in any environment; yet, little is actually known about these processes.[4]

Empirically, substantial heterogeneity in beliefs exists among young males in the National Longitudinal Survey of Youth 1997 Cohort (NLSY97) and the National Youth Survey (NYS). On average, individual beliefs about the probability of arrest for various crimes are substantially higher than official arrest rates,[5] and those beliefs are fairly stable across time for individuals. Not surprisingly, perceived arrest rates are lower, on average, among those actively engaged in crime, which is consistent with standard deterrence theory as well as the information-based model of belief updating developed here. There is little evidence that minorities believe they are more likely to be arrested than do white men, which reconciles with studies suggesting that there is little, if any, discrimination in official arrest rates across race (Tonry, 1995). Less than 5% of the heterogeneity in

[4]See Manski (1992) for a clear discussion about the importance of understanding expectations formation in studying schooling decisions.

[5]In summarizing a number of studies on perceptions, Viscusi (1998) reports that individuals tend to overestimate the risk of low probability events, which is consistent with the findings in this paper.

beliefs can be explained by differences in family background, neighborhood, or individual abilities. More surprisingly, when comparing male teenagers across states or metropolitan residential status, beliefs about the probability of arrest are not correlated with official arrest rates. While it is tempting to ignore perceptions and focus on official arrest rates when analyzing criminal deterrence (as most researchers have done), perceived arrest probabilities and *not* official state-level arrest rates are negatively correlated with criminal participation among these young males. Among men in their early twenties, there is a more noticeable difference in perceptions across urban and rural areas that is consistent with differences in official arrest rates.

While an individual's perceptions are affected by his own criminal and arrest history, the environment around him has much less of an affect on beliefs. Contrary to the "broken windows" theory developed by Wilson and Kelling (1982), perceptions are uncorrelated with neighborhood characteristics like the amount of gang activity, general lawlessness, abandoned buildings, or the presence of 'winos' on the streets. Furthermore, perceptions are not significantly affected by one's own criminal victimization, which might provide additional information about the likelihood of arrest. Instead, early beliefs about an individual's own probability of arrest are largely idiosyncratic and unrelated to average arrest rates or local conditions. Whether variation in beliefs across individuals reflects actual variation in the true probability of arrest across individuals or simple differences in beliefs is unknown. Beliefs do respond to individual-specific information, however. Individuals who engage in crime while avoiding arrest tend to reduce their perceived probability of arrest; those who are arrested raise their perceived probability. Thus, beliefs about the probability of arrest appear to be quite specific to an individual and his own interactions with the criminal justice system. More general measures of the arrest rate are not particularly important in determining an individual's beliefs about his own (individual-specific) probability of arrest. Therefore, policies that increase the average arrest rate are likely to achieve their impacts through an increase in individual interactions with the police rather than through immediate recognition of that change.

Section 2 develops a model for analyzing the interaction of perceptions and criminal behavior that focuses on an individual's own criminal choices and arrest outcomes rather than the outcomes and choices of others as in Sah (1991). The model offers new insights about lifecycle criminal decisions and the dynamic effects of changes in the actual arrest rate. It also suggests that non-criminals are pessimistic about their chances of evading arrest while criminals are optimistic.

The rest of this paper empirically examines the development of beliefs about the probability of arrest and the effect of those beliefs on actual criminal behavior using the NLSY97 and NYS. Both data sets offer different advantages for studying the interaction between perceptions and behavior. Section 3 discusses the data on criminal participation and perceptions in the NLSY97 and NYS and how beliefs vary in the population of young males. The role of belief updating is examined in Section 4, and the prediction that individuals with high perceived probabilities of arrest are less likely to engage in crime is studied in Section 5. Section 6 synthesizes the findings of this paper.

2 A Model of Crime and Perceptions

This section develops a model for analyzing the interaction of perceptions and criminal behavior from a Bayesian perspective. Individuals begin with prior beliefs about the probability of arrest for a given crime, deciding whether or not to engage in crime based on those beliefs. Their decision to engage in crime and whether they are arrested affects their future beliefs about the probability of arrest – they update their beliefs as Bayesian decision-makers. After forming new beliefs, they once again decide whether or not to engage in crime. Ex ante identical agents will draw different conclusions about the probability of arrest in response to different histories of arrest and crime. Those decisions can then be aggregated to determine how average arrest rates change over the lifecycle of a cohort and how they respond to changes in the true arrest rate.

The model complements Sah's (1991) work. His framework explores the role of crime and arrests among others in shaping individual beliefs about the probability of arrest and punishment. However, if individuals are sufficiently different in their abilities to evade arrest or if it is difficult to communicate accurate information about criminal outcomes, then information received from others about their experiences is likely to be less important than one's own criminal and arrest experiences. To simplify matters and to focus on new ideas, this section focuses exclusively on the individual's own criminal and arrest history in determining beliefs and behavior; however, both sources of information are empirically studied in later sections of the paper.

Following Becker (1968), assume that individuals choose to commit crime if the expected benefits exceed the expected costs. For simplicity, assume the benefits from each crime, B_i, are known to each individual i beforehand. Individuals also know the costs, $C_i \geq 0$, if they are arrested for the crime, but they do not know their own probability of arrest. Their prior beliefs about that probability, π_i, are described by the cumulative distribution function, $F_0(\pi)$, where $F_0(0) = 0$ and $F_0(1) = 1$ (reflecting the fact that π is a probability itself). Assuming no intertemporal effects of arrest or criminal behavior, individual i will commit crime in period t if and only if

$$B_i > C_i \int_0^1 \pi dF(\pi|H_i^t),$$

where $F(\pi|H_i^t)$ represents the distribution of arrest probabilities conditional on the information available at date t, H_i^t.[6] Letting $R_i = B_i/C_i$ and re-arranging terms yields the following decision rule for crime: commit crime if and only if the expected arrest probability is less than the benefit-cost ratio:

$$E(\pi|H_i^t) < R_i,$$

where $E(\pi|H_i^t) = \int_0^1 \pi dF(\pi|H_i^t)$.

Let d_{it} be an indicator function that equals one if individual i commits crime in period t and zero otherwise. If $R_i = X_i\gamma - \epsilon_i$, then the probability an individual with observed X_i characteristics and beliefs $E(\pi|H_i^t)$ commits crime in period t is given by:

$$Pr(d_{it} = 1|X_i, E(\pi|H_i^t)) = Pr(\epsilon_i < X_i\gamma - E(\pi|H_i^t)).$$

Conditional on observable factors affecting tastes for crime and punishment, X_i, individuals with a higher perceived probability of arrest are less likely to commit crime when unobserved tastes are independent of beliefs.[7]

Updating Perceptions

Assume that an individual's only information about the probability of arrest is given by his criminal and arrest history. He does not acquire any new information if he does not commit a crime (ignoring the possibility of arrests for crimes not committed). As a result, those not committing crime will not change their beliefs about the probability of arrest. However, those choosing to commit a crime will acquire information about actual arrest rates: they will be arrested or they will evade arrest. Their beliefs will change in response to this additional information.

To simplify notation, let $F_t(\pi) = F(\pi|H^t)$ represent the conditional cdf for π given the crime and arrest history through period t. Similarly, define $f_t(\pi) = f(\pi|H^t)$ the conditional pdf for π, and $E_t(\pi)$ the conditional expectation of π. Finally, let A_t be an indicator function equal to 1 if

[6] The model implicitly ignores any incentives to commit crime in order to learn more about the true probability. In this sense, individuals behave myopically each period. Incorporating this type of strategic behavior is straightforward and would create an additional incentive to engage in crime when beliefs are uncertain.

[7] When prior beliefs are unbiased and uncorrelated with tastes (conditional on X_i), the correlation between unobserved tastes and perceptions should be quite small in all periods.

an individual is arrested in period t and zero otherwise. Information accumulates according to: $H^t = (H^{t-1}, d_{t-1}, A_{t-1})$.[8] Among those choosing to commit crime, Bayes' Rule requires that

$$Pr(\pi|H^{t-1}, d_{t-1} = 1, A_{t-1}) = \frac{Pr(A_{t-1}|\pi, d_{t-1} = 1) f_{t-1}(\pi)}{Pr(A_{t-1}, d_{t-1} = 1)}.$$

Combined with the fact that no new information is acquired by those not engaging in crime, we obtain the conditional density function for π in period t:

$$f_t(\pi) = f(\pi|H^{t-1}, d_{t-1}, A_{t-1}) = \begin{cases} f_{t-1}(\pi) & \text{if } d_{t-1} = 0 \\ \frac{\pi f_{t-1}(\pi)}{E_{t-1}(\pi)} & \text{if } (d_{t-1}, A_{t-1}) = (1,1) \\ \frac{(1-\pi) f_{t-1}(\pi)}{1-E_{t-1}(\pi)} & \text{if } (d_{t-1}, A_{t-1}) = (1,0). \end{cases}$$

One can then update the expected probability of arrest given the conditional density:

$$E_t(\pi) = E(\pi|H^{t-1}, d_{t-1}, A_{t-1}) = \begin{cases} E_{t-1}(\pi) & \text{if } d_{t-1} = 0 \\ \frac{\int_0^1 \pi^2 f_{t-1}(\pi) d\pi}{E_{t-1}(\pi)} & \text{if } (d_{t-1}, A_{t-1}) = (1,1) \\ \frac{\int_0^1 \pi(1-\pi) f_{t-1}(\pi) d\pi}{1-E_{t-1}(\pi)} & \text{if } (d_{t-1}, A_{t-1}) = (1,0). \end{cases}$$

Since the conditional variance of π given history H^{t-1} is given by $V_{t-1}(\pi) = E_{t-1}(\pi^2) - [E_{t-1}(\pi)]^2$, this can be more simply written as:

$$E_{i,t}(\pi) = E_{i,t-1}(\pi) - \frac{V_{i,t-1}(\pi)}{1 - E_{i,t-1}(\pi)} d_{i,t-1} + \frac{V_{i,t-1}(\pi)}{E_{i,t-1}(\pi)(1 - E_{i,t-1}(\pi))} d_{i,t-1} A_{i,t-1}. \quad (1)$$

The expected probability of arrest increases when an individual is arrested and decreases when he commits a crime without being arrested. The amount of increase (or decrease) depends on both the variance and mean of the prior distribution. When there is a lot of uncertainty (i.e. $V_{t-1}(\pi)$ is high), the expected probability of arrest changes a lot in response to new information (whether that new information comes from an arrest or the lack of an arrest). When the mean prior probability of an arrest ($E_{t-1}(\pi)$) is high, individuals will show little response to an arrest while they will substantially reduce their expected probability of arrest if they manage to commit a crime without being arrested. On the other hand, when the mean prior probability of an arrest is low, individuals that are arrested will substantially revise their probability of arrest upward, while those that avoid arrest will revise their expected probability downward by much less.

Crime Over the Lifecycle and Aggregate Arrest Rates

Individuals may differ in their tastes for crime and punishment (represented by the benefit-cost ratio), their prior beliefs about the probability of arrest, and their actual probability of arrest.

[8] The i subscripts are dropped here to reduce notation.

Let individual benefit-cost ratios, R, be distributed according to the cdf $G(R)$ (with pdf $g(R)$). Assume that each individual knows his own benefit-cost ratio, that it does not change over time, and that it is independent of prior beliefs and the true probability of arrest. It is instructive to begin by studying the lifecycle crime rates of individuals who are homogeneous in both their prior beliefs, $F_0(\pi)$, and the true probability of arrest, p, but differ in their tastes for crime, R. (To avoid confusion, we use p to refer to the actual probability of arrest and π to refer to the perceived probability.)

The proportion of individuals initially abstaining from crime in period 0 is then given by $G(E_0(\pi))$. Regardless of their true probability of arrest, these individuals never engage in crime. They would only choose to engage in crime if their perceived probability of arrest were to decline. But, their beliefs never change since they do not engage in crime and, therefore, do not acquire any additional information. Law-abiding behavior is an absorbing state.

Individuals with $R > E_0(\pi)$ will initially engage in crime. Let $\mu_t(p)$ represent the criminal participation rate in period t for individuals with true probability of arrest p. Then, $\mu_0(p) = \mu_0 = 1 - G(E_0(\pi))$ is independent of the true probability of arrest. The number of individuals initially choosing to engage in crime depends only on tastes and prior beliefs, not actual probabilities of arrest. If individuals update their beliefs about the probability of arrest according to equation (1), then the fraction of individuals committing crime in all subsequent periods can be calculated. For example, in the initial period, $p\mu_0$ individuals will engage in crime and be arrested, while $(1-p)\mu_0$ will commit crime without being arrested. From equation (1), it is clear that those who are arrested will increase their mean perceived probability while those who are not will reduce theirs. As a result, all of the individuals who engage in crime without being arrested will continue to commit crime in period one. Additionally, some of those arrested in period zero may still choose to commit crime in period one if their benefit-cost ratio is greater than the new higher perceived probability of arrest. However, some of those who are arrested will drop out of the criminal sector (those initially near the margin of committing crime), never committing another crime. Overall, the crime rate in period one for individuals with a true arrest probability of p is given by

$$\mu_1(p) = (1-p)\mu_0 + p[1 - G(E(\pi|H^0, A_0 = 1, d_0 = 1))].$$

More generally, if $\hat{\pi}(H^t) = max\{E(\pi|H^0), E(\pi|H^1), ..., E(\pi|H^t)\}$ is the highest perceived probability for an individual over his entire crime and arrest history through time t, then

$$\mu_t(p) = (1-p)\mu_{t-1}(p) + p \sum_{H^{t-1}} \rho(p, H^{t-1}) \left(1 - G(max\{\hat{\pi}(H^{t-1}), E(\pi|H^{t-1}, d_{t-1} = 1, A_{t-1} = 1)\})\right),$$

where $\rho(p, H^{t-1})$ is the probability of experiencing history H^{t-1} among those with true probability of arrest p who are still engaged in crime. The fraction $1 - G(\hat{\pi}(H^{t-1}))$ represents all those with a given history H^{t-1} who have not yet dropped out of crime – they have a high benefit-cost ratio to crime. If $E(\pi|H^{t-1}, d_{t-1} = 1, A_{t-1} = 1) < \hat{\pi}(H^{t-1})$, then the additional arrest does not raise their perceived probability enough to cause them to drop out of crime. This is because they have already held the belief that arrest probabilities were higher at some earlier date, and they still chose to engage in crime. These individuals must have experienced a number of periods where they committed crime without an arrest, so their perceived probability of arrest is presently low relative to its peak. On the other hand, if $E(\pi|H^{t-1}, d_{t-1} = 1, A_{t-1} = 1) > \hat{\pi}(H^{t-1})$, then the perceived probability of arrest increases above the highest previous level and some individuals will drop out of crime. This inequality must hold for those individuals who have been arrested every period, since the perceived probability of arrest monotonically increases with each new arrest.

Clearly, $\mu_t(p) \leq \mu_{t-1}(p)$, since a non-negative number of individuals on the margin will be arrested, causing them to drop out of crime forever and there are no new entrants into crime. Thus, even with age invariant returns and costs from crime, age-crime profiles will be declining due to the accumulation of information about the probability of arrest. This force has not been noted in the literature on crime.[9]

While an increase in the arrest rate will not have any direct deterrent effects if beliefs only depend on policy-invariant priors and individual histories (e.g. individuals either do not hear about such changes or they do not believe such announcements), it will increase the likelihood of an encounter with the police among those engaged in crime. On average, arrest rates should decline as criminals face more arrests and adjust their perceived probability upwards in response. It is possible to trace the dynamic impacts of an increase in the true probability of arrest. Consider the lifecycle crime decisions of individuals under different punishment regimes. (Alternatively, consider the differences in criminal participation rates across individuals with different true probabilities of arrest.) Because initial crime rates only depend on the distribution of prior beliefs and tastes, there will be no effect of a change in p on initial crime rates for a cohort. But, period 1 crime rates will decline according to

$$\frac{d\mu_1(p)}{dp} = -\mu_0 + 1 - G(E(\pi|H^0, A_0 = 1, d_0 = 1))$$

[9] Allowing for strategic behavior designed to explicitly learn about the probability of arrest would provide additional incentives to commit crime early on. However, if individuals can acquire information about their own probability of arrest without engaging in crime, then some may choose to re-engage in crime if they receive information causing them to lower their perceived probability. This could, at least partially, offset the forces leading to declining age-crime profiles.

$$
\begin{aligned}
&= -[G(E(\pi|H^0, A_0 = 1, d_0 = 1)) - G(E_0(\pi))] \\
&\approx -g(E_0(\pi))\frac{V_0(\pi)}{E_0(\pi)}.
\end{aligned}
$$

The effect of increasing true arrest rates on crime will be greater when many individuals are at the crime margin, the variance in prior beliefs is high, and the prior expected probability of arrest is low. The period one impact on crime depends only on prior beliefs and not the true probability of arrest, since the initial crime rate, μ_0, is independent of p.

More generally, the effect of an increase in the true probability of arrest on crime rates in period t is given by

$$
\begin{aligned}
\frac{d\mu_t(p)}{dp} &= (1-p)\frac{d\mu_{t-1}(p)}{dp} - \mu_{t-1} \\
&+ \sum_{H^{t-1}} \left(\rho(p, H^{t-1}) + p\frac{d\rho(p, H^{t-1})}{dp}\right)\left(1 - G(max\{\hat{\pi}(H^{t-1}), E(\pi|H^{t-1}, d_{t-1} = 1, A_{t-1} = 1)\})\right).
\end{aligned}
$$

The first term reflects the indirect effect of a higher p on current crime through its effect on the number of individuals engaged in crime the previous period. The second term reflects the fact that a higher arrest probability reduces the number of people not arrested the previous period, who will all commit crime again. The summation term reflects the effect of increasing p on the likelihood of different histories that include an arrest in period $t-1$. Individuals with these histories may drop out of crime if their perceived probability of arrest increases above their threshold level. This term need not be negative for all periods, since a higher arrest probability could cause most 'short-term' criminals to drop out in earlier periods leaving only 'career' criminals with high values of R in later ones. In other words, an increase in the true probability of arrest could cause crime to decline among youth without having much effect on the crime rate of older individuals. Of course, the effects could also grow with age. In general, an increase in the probability of arrest will reduce crime at all ages, but the effects will vary over the lifecycle.

Changes in the true probability of arrest should not only affect the level of crime, but they should also affect the age-crime profile. The effects will differ across p-types in all but the first two periods. Higher official arrest rates should have no effect on the initial crime rate of a cohort and should reduce the criminal participation rates of all p-types by the same amount in period one. In subsequent periods, the effects are likely to differ depending on an individual's p-type.

A temporary increase in official arrest rates will have lagged effects on crime in this framework. Increasing the arrest rate in period t directly reduces crime rates in period $t+1$ (though it has no effect on crime in period t). This lowers the pool of potential criminals in all subsequent periods through the indirect effects discussed above. It also changes the likelihood of different arrest histories, raising the probability of all paths associated with an arrest in period t.

While these policy effects refer to individuals with a given set of prior beliefs and true probability of arrest, it is straightforward to compute aggregate arrest rates across all individuals by integrating over prior beliefs and true probabilities of arrest in the population. For example, suppose the true probability of arrest is given by $p = \bar{p} + \epsilon$ where $\epsilon \in [-\bar{p}, 1-\bar{p}]$ is mean zero and distributed according to the pdf $\lambda(\epsilon)$. If ϵ is independent of R, then the aggregate crime rate for those age t is given by

$$\bar{\mu_t} = \int_{-\bar{p}}^{1-\bar{p}} \mu_t(\bar{p}+\epsilon)\lambda(\epsilon)d\epsilon.$$

Initial criminal participation is independent of p, so initial crime rates are given by μ_0. Because criminal participation declines with age for any given type, aggregate crime rates will also decline with age. The rate of decline in aggregate arrest rates will depend on the distribution of true arrest probabilities in the population, since age-crime profiles depend on p. An increase in the average arrest rate, $\bar{p}$, will cause aggregate arrest rates to decline, since it should reduce crime rates among all p-types at all but the initial age. It will also affect the aggregate age-crime profile.

An Example

A simple example can be useful for showing the dynamics of belief updating and criminal activity. Suppose the benefit-cost ratio is distributed standard normal in the population and that prior beliefs are characterized by the Beta(α,β) distribution.[10] Let $n_t = \sum_{j=0}^{t-1} A_j$ denote the total number of arrests through period t. Then,

$$E_t(\pi|n_t) = \frac{\alpha + n_t}{\alpha + \beta + t}$$

is the expected probability of arrest for an individual age t who is still engaged in crime and has been arrested n_t times. If arrested, the perceived probability of arrest increases by $\frac{\beta+t+n_t}{(\alpha+\beta+t)(\alpha+\beta+t+1)}$, but if a crime goes unpunished, the perceived probability declines by $\frac{\alpha+n_t}{(\alpha+\beta+t)(\alpha+\beta+t+1)}$. It is immediately obvious that perceptions change less and less over time in response to new information (as t increases). We should, therefore, expect more variability over time in perceptions among young criminals than among seasoned veterans. Beliefs should converge to the true arrest probability for those who continue to engage in crime.

[10] That is, $f_0(\pi;\alpha,\beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\pi^{\alpha-1}(1-\pi)^{\beta-1}$ if $\pi \in (0,1)$ and zero otherwise.

We briefly explore the evolution of crime rates and perceptions over time for individuals with different sets of prior beliefs and different true probabilities of arrest. Figure 1 shows the distribution of beliefs for three types with mean perceived probabilities of arrest equal to 0.3, 0.5, and 0.7. Type II ($\alpha = \beta = 1$) individuals have diffuse priors that are uniformly distributed over the $(0, 1)$ interval. Type I ($\alpha = 3$,$\beta = 7$) individuals maintain a low initial expected probability of arrest, while Type III ($\alpha = 7$,$\beta = 3$) individuals maintain a high initial expected probability.

To isolate the role played by p in the evolution of beliefs and crime rates, Figure 2 shows average criminal participation rates for individuals with Type II (uniform) prior beliefs and different true arrest probabilities. As expected, crime rates are initially identical for all p-types, determined entirely by the mean expected prior probability of 0.5. However, the crime rate declines much more quickly with age for those with higher true probabilities of arrest. Crime rates for those with $p = 0.7$ decline by nearly one-third in just 10 periods,[11] while crime rates decline by less than 10% for those with $p = 0.3$. True arrest rates have significant impacts on crime among older individuals. Much of the discrepancy in age-crime profiles across the three different p-types is caused by the over- and under-estimation of the true arrest rate by high and low p individuals.

Figure 3 shows the crime profiles for individuals with the same three true probabilities of arrest but each with unbiased prior beliefs. Here, those with a true probability of arrest equal to 0.3 have Type I priors (with a mean probability of arrest equal to 0.3). Those with a true probability of arrest equal to 0.5 have Type II prior beliefs, and those with a true probability of arrest equal to 0.7 have Type III priors. Initial crime rates are substantially lower for those with Type III priors and higher for those with Type I priors. Because prior beliefs are unbiased for all three types, the perceived probability of arrest does not change very much over time for most individuals. As a result, crime declines very little. The slightly larger decrease in crime for the Type II individuals with $p = 0.5$ is due to their higher initial variance in beliefs (0.083 vs. 0.019). Individuals with a higher variance of beliefs adjust their perceptions more in response to new information as show in equation (1).

Figure 4 displays the evolution of average perceived probabilities of arrest for each of the three types depending on whether they choose to commit crime that period.[12] In all but the initial period, criminals hold lower perceived probabilities of arrest, on average, than their true probability, while non-criminals hold higher perceived probabilities. Criminals are 'optimistic' and non-criminals

[11] The length of a period should correspond to the amount of time between criminal opportunities, which is likely to vary depending on the crime.

[12] In creating Figure 4, 200,000 arrest profiles were randomly drawn for each type.

'pessimistic' about their chances of evading arrest. The increase in the perceived probability by non-criminals is entirely due to changes in the composition of that group, since individuals not engaged in crime do not change their beliefs. New non-criminals have higher perceived probabilities than those who never commit crime, driving up the conditional mean probability of all non-criminals. The average perceived probability of criminals declines initially, since most of those continuing to engage in crime have avoided an arrest while those who have been arrested (and hold high perceived probabilities) drop out of crime. At some point, however, most individuals who will drop out of crime already have. Then, the distribution of criminals is relatively stable and the average perceived probability of arrest increases since those who are arrested tend to raise their perceived probability more than those who avoid an arrest. This is because their perceived probability of arrest is generally lower than the true probability and an arrest has a greater impact on beliefs than avoiding an arrest. The (unconditional) average perceived probability of arrest for each type is generally greater than that type's true probability of arrest in all but the initial period. Thus, even if individuals begin with unbiased beliefs, they are likely to become pessimistic over time. However, the degree of pessimism is quite small in these examples.

Figure 5 aggregates beliefs across types assuming each type represents one-third of the population. The average true probability is 0.5; however, the average true probability of those engaged in crime (the official arrest rate represented by the dotted line) is lower by about 0.03 since types with a low probability of arrest engage in crime at a higher rate. A shift in the distribution of types towards more Type III individuals would inflate this discrepancy. The average perceived probability among non-criminals and the full population are both higher than the official arrest rate, while the average perceived probability among criminals is lower. Most of the difference in beliefs across criminal status is due to differential rates of criminal participation across the three types of individuals; although, within type differences also contribute as shown in Figure 4.

Policies that alter the arrest rate will have dynamic effects on criminal participation through belief updating. For example, the impacts of temporary and permanent increases in the true probability of arrest on crime rates are shown separately for each type in Figure 6. Not surprisingly, a permanent increase of 5% in the true probability of arrest for each type reduces crime in all subsequent periods. Much of the early impact can be reproduced with only a single-period increase in the arrest rate at time zero. While the impact of a permanent increase in the arrest rate continues to grow over time, the effect of a temporary change is fairly constant after only a few periods. In comparing the impacts across types, the impacts are greater for the higher crime (lower

p) types. Among Type I and II individuals, a 5% increase in the true arrest probability reduces criminal participation by nearly 1% after ten years. The effects are about half as large for Type III individuals.

This framework and the accompanying example show that incorporating beliefs about the likelihood of arrest in a criminal choice model can lead to interesting dynamic responses to changes in the probability of arrest that are frequently ignored. It can also help explain why crime declines with age, predicting that individuals drop out of the criminal sector once their perceived probability of arrest becomes too high for their tastes. Additionally, it explains why criminals may be optimistic about their chances of evading arrest when non-criminals are pessimistic. Overall, the average perceived probability of arrest is likely to be greater than official arrest rates.

A more complete model would allow for changes in the benefit-cost ratio of crime over the life-cycle to reflect changes in the opportunity costs of crime. This is certainly an important component of the declining age-crime profile. Allowing for randomness in the benefit-cost ratio of each criminal opportunity would help explain why criminals do not necessarily commit crime continuously before quitting completely. In such an environment, the propensity to commit crime would follow the same patterns described above, since individuals would still choose to commit crime when the benefit-cost ratio is greater than the perceived probability of arrest. The perceived probability of arrest would only change after periods in which individuals choose to commit a crime. Finally, the acquisition of information apart from one's own criminal and arrest history, as in Sah (1991), may also be important. In the sections that follow, we examine the empirical importance of these issues as well as the main predictions of the model.

3 Crime and Perceptions

NLSY97 Data

The NLSY97 contains a sample of 9,022 individuals (4,621 males) ages 12-16 in 1997. While the survey is ongoing, only a panel for 1997 and 1998 is currently available. 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 and various punishments for auto theft.[13]

[13] Specifically, the survey asks: "What is the percent chance you would be arrested if you stole a car?" It also asks three separate questions about the outcome of arrest: "Suppose you were arrested for stealing a car, what is the percent chance that you would [be released by the police without charges or dismissed at court, pay a fine and be released, serve time in jail]?"

The extent of criminal activity among young males in the NLSY97 is shown in Table 1. Around 10% of all young males report an arrest for some offense prior to the 1997 survey. Slightly more blacks and hispanics report an arrest in comparison with young white males. Roughly, 2-3% report an arrest for theft. About 40% of young males report having committed a theft, with blacks reporting the least involvement and whites the most. Approximately 10% of all three racial/ethnic groups report stealing something worth more than $50. Less than 2% of the sample reports having committed auto theft. While all races report similar rates of stealing something worth more than $50, the average number of thefts among those engaged in theft was much lower among whites and hispanics than among blacks. The pattern of similar participation rates for all races and greater involvement by blacks conditional on participation is consistent with the findings of Elliott and Ageton (1980).

For every person who stole something, 0.07 persons were arrested for a 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 among individuals stealing something worth more than $50, we can approximate the arrest rate for theft by race/ethnicity. Between 0.22 (hispanics) and 0.31 (whites) 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 is given at the bottom of the table, which reports the total number of arrests for theft per reported theft of more than $50. These rates range from 0.07 for blacks to 0.09 for whites. According to these figures, less than one out of every ten thefts of greater than $50 results in an arrest, and minorities are *less* likely to be arrested than whites. A number of caveats should be noted. First, some individuals may be arrested even though they have not committed a theft – this would bias arrest rates upward. Second, some arrests may be for thefts of less than $50 in value, again biasing these estimates upward. Third, both arrests and crimes are self-reported, both of which may be under-reported. To the extent that individuals under-report crimes more than arrests, these estimates will be biased upward. Unless arrests are substantially under-reported compared to actual thefts of greater than $50, these arrest rates should over-estimate true arrest probabilities; though the amount of bias is likely to be small.

While these rates are substantially lower than official clearance rates[14] for burglary, larceny-theft, and motor-vehicle theft (Sourcebook of Criminal Justice Statistics, 1998), they accurately reflect official arrest rates after adjusting for non-reporting by victims. Table 2 shows clearance

[14] An offense is 'cleared by arrest' when at least one person is: (1) arrested; (2) charged with the commission of the offense; and (3) turned over to the court for prosecution.

rates, arrests per known offense, rates of victim reporting to the police, and arrest rates adjusted by reporting rates for five index crimes in 1986 and 1997.[15] The final column, the adjusted arrest rate, suggests that 5-10% of property crimes result in an arrest. Thus, the youth surveyed by the NLSY97 are arrested at rates that closely correspond to official nationwide arrest rates.

Beliefs about the probability of arrest are likely to depend not only on enforcement variables but also on the ability of an individual to evade detection. In studying why individuals hold different beliefs about the likelihood of arrest, it is, therefore, important to consider characteristics which might be correlated with criminal abilities as well as those which may affect opinions about law enforcement. Figure 7 reports the 1997 distribution of the perceived probability of arrest for auto theft among teenage males in the NLSY97. In general, most youth report much higher perceived probabilities of arrest than is reflected in national arrest rates or in the actual arrest rates for crimes committed by this sample, which are much closer to around 10%. The figure shows strong focal points at probabilities of 0, 50, 75, and 100%.

Young males from all racial and ethnic backgrounds tend to report a relatively high probability of arrest as shown in Table 3. While most previous research has shown that official arrest rates do not vary across race (Tonry, 1995), popular discussion might cause one to think that minorities believe they are more likely to face arrest and serious punishment. This does not appear to be the case.[16] Row A of the table shows that both young black (49%) and hispanic (54%) males tend to have *lower* perceived probabilities of arrest for auto theft than the average young white male (65%). Conditional on arrest, however, all three groups hold very similar views about the probability of receiving different punishments (see Table A-1), believing a fine to be the most likely outcome of arrest and release without charge least likely.

The fact that perceived probabilities of arrest are substantially higher than the true arrest rates discussed earlier (see Tables 1 and 2) does not necessarily imply that individuals overestimate their own probability of arrest. Individuals that 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, even teenage males engaged in crime report high probabilities of arrest. Panel (B) of Table 3 reveals probabilities for young males who reported stealing something worth more than $50; panel (C) shows perceptions for young males who have committed auto theft;

[15] Arrests, offenses known to the police, and clearance rates are taken from the FBI's Uniform Crime Reports, while reporting rates to the police are given by the Bureau of U.S. Department of Justice, Criminal Victimization in the United States.

[16] From a different perspective, police may discriminate against minorities by failing to pursue perpetrators who victimize them. Since most criminals victimize others like them, this would result in lower real and perceived arrest rates among minorities.

and panel (D) calculates average perceived probabilities using the number of thefts (of over $50) committed by each individual to weight the observations. Panel (D) best 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 should equal the sample arrest rate.

Among teenage males who have stolen something worth more than $50, whites believe that their probability of facing arrest is about 11% higher than hispanics or blacks. Among auto thieves, hispanics have the lowest perceived probability, but sample sizes are quite small. Young white males who have been arrested consider their chance of arrest for auto theft to be high (around 60%) relative to blacks (45%) and hispanics (51%). There is little evidence to support the proposition that blacks and hispanics feel discriminated against in terms of facing higher arrest rates for auto theft.

In general, teenage males that are more involved in crime tend to predict better chances of evading arrest. These differences in perceptions can be attributed to a number of potential factors: (1) individuals who hold optimistic views about their chances of success (perhaps, because they have successfully avoided arrest in the past) should be more likely to commit crime; (2) individuals who are better at evading arrest (and truly face lower probabilities of arrest and punishment) can be expected to commit crime at higher rates (all else equal); and (3) individuals not engaged in crime have little incentive to figure out the true probability while those engaged in crime should have more accurate views since such information is crucial for their 'work.' Still, it is surprising that even those engaged in auto theft report an average expected arrest rate of greater than 30% (as high as 50% for whites).

An obvious explanation for the discrepancy in beliefs and true arrest rates is that individuals mis-interpret the question. Rather 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 for 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 (27% 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 only choose to steal cars that offer a substantially lower probability of arrest. In this case, reported arrest probabilities would be greater than the official arrest rate. It is possible to envision many stories that reconcile differences in reported beliefs about the probability of arrest and official arrest rates.

However, most explanations are consistent with a world in which differences in reported beliefs across people reflect true differences in the perceived probability of arrest. As long as this is true, there is likely to be an important informational content to reported beliefs that can be used to study differences in behavior.

Table 4 uses linear regression to examine the importance of individual characteristics, family background, geographic variables, and state-level arrest rates in explaining the perceived probability of arrest in 1997. Column 1 examines how perceptions vary by age, race, and residential location. As in Table 3, blacks and hispanics report a lower probability of arrest than whites even after controlling for age, region of residence, and residence in a Metropolitan Statistical Area (MSA). Teenagers living in an MSA do not report lower perceived probabilities of arrest even though clearance rates for auto theft are twice as high in rural communities as in urban or suburban areas. Column 2 includes a measure of the state arrest rate for 1997 (number of arrests per crime committed). Surprisingly, actual arrest rates are *negatively* correlated with the perceived probability of arrest, suggesting that youth living in states with higher arrest rates report that they are less likely to get arrested themselves. The negative correlation remains when controlling for various family background characteristics in column 3 (or without conditioning on any variables). Whether the youth lives with both his natural parents, whether his mother was a teenager at birth, family income, and the presence of gangs in the neighborhood do not affect an individual's reported beliefs about the probability of arrest. Of the individual characteristics other than race, only the effects of Peabody Individual Achievement Test (PIAT) scores for math (in percentiles),[17] are statistically significant, suggesting a positive relationship between the perceived probability of arrest and math ability. (Counter to an 'ability to evade' arrest hypothesis, a 10% higher PIAT score is associated with a 1% higher perceived chance of arrest.) After controlling for individual backgrounds, however, the effects of race decline substantially. Still, the results suggest that blacks report an 8.6% lower probability of arrest than whites. Differences between Hispanic and white reports are not statistically significant.

Table A-2 reports similar estimates for the likelihood of different punishments conditional on arrest. Blacks also believe that they face a lower probability of spending time in jail once arrested, while hispanics feel that they are more likely to be released without charge or with a fine if arrested. Individuals from families with a higher income consider themselves less likely to face fines or jail

[17]Note that PIAT scores are only observed for individuals with less than 10 years of schooling–nearly everyone age 16. To maintain the representativeness of the sample, all individuals age 16 are dropped from regressions including PIAT scores, making the sample representative of males ages 12-15.

time if arrested. While the magnitude of this effect is small, it may suggest that delinquent youth from high income families believe that they can buy their way out of trouble.

The considerable variation in perceptions is not well explained by these characteristics – the R^2 statistics for these regressions are all less than 0.04. It is somewhat surprising how little of the differences in beliefs can be predicted from rich measures of family background, geographic location, age, race, and ability. Yet, these perceptions are fairly stable over time as seen in Figure 8, which shows the distribution of changes in perceptions from 1997 to 1998. More than 30% of respondents do not change their beliefs about the probability of arrest. The correlation in perceptions from one year to the next is roughly 0.24.

NYS Data

The NYS contains a random sample of 1,725 individuals ages 11-17 in 1976. Individuals were surveyed annually from 1976-1980, 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).[18] Data regarding family background and geographic location are also available. Surveyed men were ages 18-24 in 1983.

Respondents were asked how many times they engaged in numerous delinquent and criminal activities over the sample period. Table 5 reports the extent of criminal activity and arrest records over 1984-86. Since most individuals are in their early twenties, criminal participation is much lower than for the younger sample in the NLSY97. Yet, 22% still report stealing something worth less than $5, and 9% report physically attacking someone. Substantially fewer individuals engage in more serious property and violent crimes. Nearly 12% report an arrest over the three-year span, although many of those arrests are for minor crimes. Only 1.1 percent are arrested for a property crime and .7% are arrested for a violent crime.[19]

Measures of sample arrest rates can be calculated from the information on criminal behavior and arrests. When dividing the number of arrests for property crimes by the total number of break-ins and thefts greater than $50 reported in 1983 and 1986, average arrests per property crime are slightly under 5%. A similar arrest rate is obtained for violent crime when dividing

[18] Surveys for 1983 and 1986 actually took place early in 1984 and 1987, respectively. Perceptions questions, therefore, refer to beliefs at the end of 1983 (1986) and beginning of 1984 (1987). Criminal participation (and most other) questions explicitly asked 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, though in considerably less detail than questions related to 1986.

[19] 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 included crimes such as prostitution, vagrancy, panhandling, etc.

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 official arrest rates in the U.S. population as reported in Table 2, especially for violent crimes. However, both the number of crimes and number of arrests in this sample are quite small as seen in Table 5. 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 a number of different crimes.[20] The distribution of reported probabilities of arrest in 1983 is shown in Figure 9. Table 6 reports average perceived probabilities of arrest in the NYS for five crimes: stealing something worth $5 or less, stealing something worth more than $50, breaking into a building or vehicle, using force to get money or things, and attacking someone to hurt or kill them. As with teenage boys, perceived arrest rates are substantially higher than official arrest rates in the U.S. (shown in Table 2). Yet, the ranking of crimes by perceived arrest probability from most to least likely does correspond to the ranking of actual arrest rates. Unlike with the sample of teenage boys, however, black and hispanic men report higher perceived arrest probabilities for property crimes than do white men; although, the differences are quite small for all but petty theft.[21]

Table 7 examines whether perceptions vary across criminals and non-criminals. Specifically, the first column reports perceived probabilities for those who did not commit the crime in question, while the second column reports perceived probabilities for those who did. The final column weights perceived probabilities by the number of times an individual 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, especially among those engaged in small theft and assault (attacking someone). Weighting beliefs by the number of crimes lowers perceived probabilities even more for most crimes; though small theft is a noticeable exception. Regardless of the sample, perceived probabilities of arrest are high compared to average arrest rates in the U.S.

The effects of age, race, family background, neighborhood characteristics, and urban status

[20]Specifically, the survey asks five distinct 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, use force (strongarm methods) to get money or things from other people, attack someone with the idea of seriously hurting or killing him/her]. What are the chances you would be ticketed/arrested?"

[21]Unfortunately, it is impossible to determine whether differences across the NYS and NLSY97 sample are due to differences in time period (mid-1980s vs. late 1990s), differences in respondents' age (early teens vs. mid-twenties), or differences in the types of crimes studied.

on perceptions among young men are reported in Table 8. The perceived probability of arrest is declining with age for property crimes. This is most likely due to learning about the true probability of arrest, as expanded upon further in the next section. Even after controlling for other background characteristics, blacks hold a significantly higher perceived probability of arrest than whites for property crimes, but not for violent crimes. Hispanics also hold higher probabilities, though they are not significantly different from those of whites given the small sample size. Men who grow up in intact families[22] and have more educated mothers or fathers think that their likelihood of arrest is lower, on average.

Consistent with official arrest patterns, men in rural areas hold higher perceived probabilities of arrest than those in urban communities; though the difference in perceptions is smaller than official differences. So, while the perceptions of teenage males do not appear to be positively correlated with true arrest rates, the perceptions of men in their twenties are.[23] To the extent that prior beliefs are largely independent of actual arrest rates, it is reasonable to expect little correlation between beliefs and actual arrest rates at young ages. Similarly, it is not surprising that the beliefs of older individuals, who have accumulated more information about actual arrest rates, are more consistent with official arrest patterns.

Finally, the coefficients on neighborhood crime and disarray are small and insignificant. Young men living in neighborhoods characterized by decay and lawlessness do not view their chances of evading arrest any differently from those living in cleaner and safer environments. Based on the "broken windows" theory of Kelling and Wilson (1982), we might have expected a negative correlation between these neighborhood characteristics and the perceived probability of arrest. These results cast doubt on the importance of observable neighborhood decay in influencing behavior through its effects on the perceived probability of arrest or punishment.

While there is substantial heterogeneity in beliefs, rich background and neighborhood covariates explain very little of the variation in perceptions for all five crimes. Perceptions are largely idiosyncratic and difficult to explain. Yet, they are fairly stable. Figure 10 shows the distribution of changes in beliefs from 1983 to 1986 for the sample. Around 20% of the sample does not change its reported probability of arrest. About 60% changes its perceived probability by twenty percent or less over three years. Fewer than 5% of the young men revise their probabilities up or down by more than fifty percent. Correlations between 1983 and 1986 perceptions are typically around

[22] An individual grew up in an intact family if he was living with both natural parents in 1976.

[23] State of residence is unknown in the NYS, so perceptions cannot be compared with official state arrest rates as in the NLSY97.

one-third. In fact, these correlations are greater than the correlation in perceptions for the younger NLSY97 males across adjacent years. This pattern is consistent with the model of Section 2 in which individuals revise their beliefs less and less in response to new information as they accumulate more and more information (with age) about the probability of arrest (i.e. as individuals become more certain and the variance in beliefs declines).

4 Information-Based Belief Updating

This section more closely examines what causes individuals to change their perceptions. In a world in which individuals do not know the probability of arrest with certainty, one might expect them to revise their beliefs about that probability over time as they acquire new information. They learn firsthand about their own probability of arrest if they participate in crime. If arrested for a crime, they should revise their perceived probability upwards. Otherwise, they should revise it downwards. Additionally, individuals may learn more about local arrest rates from information provided by friends or acquaintances involved in crime. They may also acquire information about arrest probabilities as victims of crimes that may or may not lead to an arrest. Even if individuals do not act as perfect Bayesian decision-makers, any reasonable information-based model of belief updating will yield these predictions.

Rather than impose the Bayesian structure of Section 2 on the data, a more general structure of updating is examined. In the NLSY97, we model the perceived probability of arrest for auto theft in 1998 as a function of the perceived probability in 1997, criminal behavior and arrest experiences between the 1997 and 1998 interviews, and other individual and family characteristics that may affect beliefs or the information individuals acquire. Table 9 reports OLS coefficient estimates for two specifications. We focus on coefficients relevant to belief updating. In the first specification, indicators for criminal involvement and arrests between the two survey years are included, while the second specification includes the actual number of times individuals committed various crimes and were arrested over that period. Both specifications are in agreement: individuals who participate in crime are likely to report a lower perceived probability of arrest (conditional on prior beliefs and the arrest outcome). However, those who are arrested for a crime are likely to have a higher perceived probability. For example, a young male who commits ten attacks on others over the course of one year (committing no other crimes) and is not arrested will have a perceived probability of arrest that is lower by five percentage points than another male who had the same prior perceived probability but commits no crimes. But, if the male committing 10 attacks is arrested once, his probability will be lower by only one percentage point; if he is arrested twice, it will be higher by three percentage points. Thus, young males change their beliefs in response to their behavior and their experiences with police.

A similar analysis is performed with young men in the NYS, modeling perceived probabilities of arrest at the end of 1986 as a function of 1983 beliefs, involvement in crime in 1984-86, and whether or not the individual was arrested in 1984-86. Table 10 reports coefficient estimates for each of the five crimes studied in the NYS. We focus attention on rows two through four. Estimates in the second row correspond to coefficients on indicator variables for whether or not an individual participated in that type of crime between survey dates (e.g. in column 1, the indicator is one if the individual reported stealing something worth less than $5 and zero otherwise). As with younger males, men report significantly lower perceived probabilities of arrest for four of the five crime categories at the end of 1986 if they engaged in that type of crime in 1984-86. While the estimated coefficient on criminal participation is strongly negative for 'use of force' as well, the standard error is quite large due to the very low participation rate in that crime. The estimated effects are smallest for petty thefts. This is consistent with the fact that more information is likely to have already been acquired about the probability of arrest for that crime compared to the other crimes, which are engaged in less frequently. Thus, any additional information is likely to have less of an impact on perceptions for petty theft. Row 4 shows that those who were arrested for any crime (after 1983) had significantly higher perceived probabilities for theft in 1986 as predicted.[24] Coefficients on arrest are not significant for the final three types of crime, however. This may be due to the fact that many of the reported arrests are for minor crimes (e.g. loitering, vagrancy, etc.), while these crimes are more severe. Table 11 controls for whether individuals are arrested for property or violent crimes rather than any type of arrest. While the estimated coefficients on criminal participation do not change qualitatively, the effects of arrest are more pronounced and significant for the more severe crimes.[25]

One might also expect individuals who have been victimized to adjust their beliefs, since they are likely to learn whether or not the perpetrator is ever arrested. In a world in which all individuals face identical probabilities of arrest, information as a victim should be as useful as information as

[24] Unfortunately, it is not possible to condition on the actual number of crimes and arrests as with the NLSY97 sample, since only participation is known for most of the sample in 1984 and 1985 (non-survey years). Individuals who are arrested are likely to have engaged in more crime than those reporting participation in crime but no arrest, which may explain why the net effect of criminal participation and an arrest (adding the two coefficients together) is typically around zero rather than positive.

[25] Standard errors on arrest coefficients are also larger for all crimes, since there are fewer arrests for violent and property crimes in the sample.

a perpetrator. Unfortunately, the data do not record whether someone was arrested for the crime, but it is reasonable to assume that no arrest was made in most cases given the low average arrest rates reported in Table 2. Then, we should expect, on average, that individuals will adjust the probability of arrest downward after a victimization. In regressions analogous to those in Tables 10 and 11 that also control for whether the individual was the victim of a theft in the year prior to the 1986 survey, the results suggest that perceptions do not change in response to the victimization. That is, the coefficients on victimization are small and statistically insignificant for all crimes. This suggests that individuals put little weight on the information provided by arrest histories from others – the emphasis of Sah's (1991) theory. Arrest probabilities may be too individual-specific such that information about another criminal's success or failure is not very useful in determining one's own arrest probability.

Altogether, these estimates strongly suggest patterns consistent with belief updating among respondents that is based on their own history of interaction with the criminal justice system. When young men participate in crime, they tend to lower their perceived probability of arrest if they evade arrest. If arrested, they raise their perceived probability. One could potentially explain the first finding by arguing that individuals chose to commit crime between sample periods because they had already (for some exogenous reason) lowered their perceived probabilities (but were unable to report those new perceptions until surveyed the second time). Or, those engaged in crime could have gained experience at crime, lowering their true (and perceived) arrest probability. However, such scenarios cannot explain why those arrested between sample dates maintain higher perceived probabilities of arrest at the time of the second interview. An information-based model of belief updating like that of Section 2 can readily explain both findings. The model of Sah (1991), which relies on information provided by the crime and arrest histories of others, finds less support in the data.

5 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. Rational choice theory and the model of Section 2 suggest that (holding all else constant), individuals facing a higher probability of arrest and/or punishment should commit less crime. Of course, reported perceptions may differ from true beliefs about these probabilities, which would make it difficult to detect a relationship between reported perceptions and criminal behavior. Fortunately, such a relationship can be examined empirically using the NLSY97 and NYS.

Using the NLSY97, a probit model is used to estimate the effect of the perceived probability of arrest on participation in various self-reported crimes after controlling for individual, family, neighborhood, and geographic characteristics.[26] Since 1997 perceptions cannot have been affected by subsequent criminal behavior (and their arrest outcomes), we explore the effects of 1997 perceptions on crime in the following year. Table 12 reports the estimated effect of a 10% increase in the perceived chance of arrest on criminal/delinquency participation decisions.

A quick glance at the first column of the table reveals a negative relationship between the perceived chance of arrest and participation in crime. A 10% increase in the perceived chance of arrest is associated with a 0.001 decline in the average probability that a young male steals a vehicle. Though not statistically significant, this reflects a large (4.5) percentage decline in auto theft participation rates as seen in the final column. To the extent that perceptions about auto theft arrest rates are correlated with perceptions about arrest rates and punishments for other crimes, we would expect a negative correlation between auto theft arrest probabilities and those crimes as well. Table 12 supports this speculation. The reduction in thefts is both sizeable and statistically significant. A 10% rise in perceived auto theft arrest rates is associated with a 4% lower participation rate in thefts of over $50. A high perceived probability of arrest for auto theft is also associated with lower participation in property destruction, drug sales, and assault.

It is possible that perceptions of arrest rates are correlated with more general unobserved preferences for risk and crime. Then, these estimated relationships would capture both the deterrent effect of a higher perceived probability of arrest and unobserved heterogeneity in preferences that is correlated with those perceptions. However, the final two rows of the table suggest that the correlation between perceptions and minor delinquent activities like smoking and drinking are quite small – much smaller than the correlations between perceptions and more serious crimes (see the final column of the table). This suggests that much of the correlation between perceptions and serious crimes represents actual deterrent effects.

Treating these estimates as the deterrence effect of arrest probabilities, it is possible to make a number of interesting comparisons.[27] Combining the estimated coefficients in Table 4 (column 3) with those of Table 12 generates predicted racial differences in crime rates due to different

[26] All probits control for age, age-squared, race, ethnicity, MSA status of current residence, whether or not the youth lives with both his natural parents, whether or not the youth's mother was a teenager at birth, PIAT scores for math, region of residence, whether or not there are gangs in the youth's neighborhood or school, and the perceived probability of arrest in 1997.

[27] Attenuation bias associated with measurement error in perceptions is likely to lead to an under-statement of the effects discussed here.

perceptions about arrest rates. For example, the estimated 8.6 percentage point difference in perceived arrest probabilities between whites and blacks translates into a 3.8% higher participation rate in auto theft by blacks. Hispanics are predicted to have a 1.1% 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 75th and 25th percentiles in PIAT math scores is 2.2%. These predicted differences are sizeable and have, until now, been unrecognized in the literature on crime. Variation in criminal participation rates across individuals may be due to differences in perceptions (and information) just as much as differences in tastes or abilities.

From Tables 9 and 12, we can calculate the effect of an arrest on subsequent criminal behavior through its effect on perceptions. These estimates suggest that a single arrest raises the perceived probability of arrest for auto theft by about 4%, which should reduce subsequent participation in auto theft by around 2%. This estimate differs from those typically discussed in terms of deterrence. Standard analyses assume that individuals know the true probability of arrest and that increasing arrest rates directly deters crime. However, this analysis suggests that perceptions are important for determining crime. By increasing arrest rates, more individuals will be arrested. This should cause these additional arrestees to respond by revising their perceived arrest probabilities upward and, therefore, lowering their subsequent crime. Of course, information about arrest rates may disseminate more generally, as friends and acquaintances of criminals and victims learn from the experiences of others around them. However, evidence reported earlier suggests that this is likely to be less important.

Three additional specifications were explored but are not reported due to the similarity in findings. Specifications which allow for differential effects by race and ethnicity do not reveal statistically different effects of the probability of arrest by race/ethnicity on crime (except in regards to smoking for which blacks show less of a 'response'). Thus, males show similar responsiveness to perceived law enforcement effectiveness regardless of race and ethnicity. Specifications which include the conditional probabilities for being fined or put in jail (in addition to the probability of arrest) yield similar estimates for the impact of arrest probabilities.[28] Finally, specifications that also included the state-level official arrest rate in addition to (or instead of) the perceived probability were explored. The coefficient on state-level arrest rates was small and insignificantly different from zero for all crime and delinquency measures except drinking alcohol (which yielded

[28]For a few crimes (property damage, smoking marijuana, and drinking), the conditional probability of spending time in jail had a negative effect on behavior as one might expect. In general, however, there is a high degree of multicollinearity between the perceived probability of arrest and the perceived likelihood of a severe punishment, which makes estimating the effects of both probabilities difficult.

a small but significant positive rather than negative coefficient). Thus, perceptions among the teenage males explain criminal behavior, but official arrest rates do not.

A similar analysis can be employed using adult men in the NYS. Table 13 reports coefficient estimates from probit models for criminal participation (after 1983) controlling for age, family background, and urban status.[29] The perceived probability of arrest in 1983 (for each respective crime) negatively affects all five crimes, although only the coefficients for small thefts, break-ins, and attack are significantly different from zero. While not shown, the effects are quite similar even when conditioning on criminal behavior in 1983 (prior to the perceptions measure). Furthermore, controlling for parental and peer approval levels for crime as well as the individual's own moral attitudes towards crime does not noticeably change the estimates. These additional specifications suggest that permanent unobserved tastes and abilities are not driving the results.

Table 14 reports the average effects of a 10% change in the perceived probability of arrest on participation in each type of crime. As in Table 12, the final column reports the percentage change in criminal participation. By that metric, perceptions are most important in determining break-ins and physical attacks, but they are quite important for all crimes except the more substantial thefts. Estimates from Table 10 reveal that individuals who are arrested increase their perceived probability of arrest for small thefts by about 8%. When combined with the effects of perceptions on criminal participation (Table 10), this suggests that arresting a young man will reduce his probability of committing another such theft from 0.22 to about 0.20 (or about 7.6%) over the next three years. Similar analysis suggests that such an arrest will reduce larger thefts by about 1.7%, break-ins by 10.2%, use of force by 4.5%, and attacks by less than 1%. (Using estimated perception responses from Table 11 rather than Table 10 yields substantially larger impacts of 2.8%, 38.2%, 15.1%, and 14.7%, respectively, for each of these crimes).

6 Conclusions

This paper has examined the perceptions held by young males regarding the criminal justice system. While most males report a probability of arrest that is higher than official arrest rates would suggest, there is considerable heterogeneity in those beliefs. For example, criminals hold significantly lower perceived probabilities of arrest than do non-criminals. There is little evidence, however, that minority groups believe that they are more likely to be arrested or face stiffer penalties if arrested.

[29] In addition to 1983 perceptions, regressors include age and indicators for whether the respondent was black or hispanic, grew up in a family earning less than $10,000 in 1976, lived with both parents in 1976, mother graduated from high school, father graduated from high school, lived in a central city, and lived in a rural area.

In fact, black teenagers tend to view their chances of evading arrest and strict punishment to be better than whites and hispanics. Beliefs about the probability of arrest are not affected by local neighborhood conditions as implied by the 'broken windows' theory of Kelling and Wilson (1982). Among teenage males, the differences in perceived probabilities of arrest are not explained by differences in state-level official arrest rates or differences in the probability of arrest between urban and rural areas. However, urban-rural differences in official arrest rates are partially reflected in perceptions among young men in their twenties.

While perceptions are not well explained by standard background measures, they do appear to change with new information. Young males who commit crime and get away with it reduce their perceived probability of arrest. Those who are arrested raise their perceived probability. An individual's own crime and arrest history is an important determinant of perceptions. On the other hand, perceptions show no response to information about the likelihood of arrest provided by others who victimize them. A reasonable interpretation is that arrest probabilities are idiosyncratic, so that knowledge about another's success or failure at crime provides little information useful for predicting one's own likelihood of success.

Most importantly, young males act on their perceptions. Those who view their chances of arrest to be high are less likely to engage in crime. Data on perceptions and criminal behavior are well explained by the model developed in this paper in which individuals decide whether or not to engage in crime based on their perceived probability of arrest and in which that perceived probability changes over time in response to their own crime and arrest histories. While most of the literature on criminal deterrence assumes that individuals know true arrest rates and that an increase in arrest rates will immediately deter crime, this paper suggests that it may take time for individuals to recognize change. As information about higher arrest rates disseminates, individuals will respond by reducing their participation in crime. Responses to changes in enforcement are likely to differ across individuals with different crime and arrest histories, and the full impacts of any policy will be realized over many years. Age-crime profiles are likely to change as well.

References

[1] A. Banerjee. A Simple Model Of Herd Behavior. *Quarterly Journal of Economics*, 107:797–817, 1992.

[2] G. Becker. Crime and Punishment: An Economic Approach. *Journal of Political Economy*, 73:169–217, March/April 1968.

[3] S. Bikhchandani, D. Hirshleifer, and I. Welch. A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. *Journal of Political Economy*, 100:992–1026, 1992.

[4] A. Blumstein, D. Nagin, and J. Cohen. *Deterrence and Incapacitation: Estimating the Effects of Criminal Sanctions on Crime Rates.* National Academy of Sciences, Washington, DC, 1978.

[5] S. Cameron. The Economics of Crime Deterrence: A Survey of Theory and Evidence. *Kyklos*, 41:301–23, 1988.

[6] I. Ehrlich. Participation in Illegitimate Activities: A Theoretical and Empirical Investigation. *Journal of Political Economy*, 81(3):521–65, May/June 1973.

[7] I. Ehrlich. On the Usefulness of Controlling Individuals: An Economic Analysis of Rehabilitation, Incapacitation, and Deterrence. *American Economic Review*, 71(3):307–22, June 1981.

[8] D. Elliott and S. Ageton. Reconciling Race and Class Differences in Self-Reported and Official Estimates of Delinquency. *American Sociological Review*, 45:95–110, Feb. 1980.

[9] J. Grogger. Certainty vs. Severity of Punishment. *Economic Inquiry*, 29:297–301, 1991.

[10] S. Levitt. Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime. *American Economic Review*, 87(3):270–90, June 1997.

[11] S. Levitt. Juvenile Crime and Punishment. *Journal of Political Economy*, 106(6):1156–85, Dec. 1998.

[12] S. Levitt. Why Do Increased Arrest Rates Appear to Reduce Crime: Deterrence, Incapacitation, or Measurement Error? *Economic Inquiry*, 36:353–72, July 1998.

[13] K. Maguire and A. Pastore, editors. *Sourcebook of Criminal Justice Statistics - 1998.* U.S. Department of Justice, Bureau of Justice Statistics, U.S. Government Printing Office, Washington, DC, 1998.

[14] C. Manski. Adolescent Econometricians: How Do Youth Infer the Returns to Schooling? In C. Clotfelter and M. Rothschild, editors, *Studies in Supply and Demand of Higher Education*, chapter 2. University of Chicago Press, Chicago, 1992.

[15] W. Minor and J. Harry. Deterrent and Experiential Effects in Perceptual Deterrence Research: A Replication and Extension. *Journal of Research in Crime and Delinquency*, 19:190–203, 1982.

[16] S. Myers. Estimating the Economic Model of Crime: Punishment vs. Deterrent Effects. *Quarterly Journal of Economics*, 98:157–66, 1983.

[17] R. Paternoster, L. Saltzman, G. Waldo, and T. Chiricos. Perceived Risk and Social Control: Do Sanctions Really Deter? *Law and Society Review*, 17(3):459–77, 1983.

[18] I. Piliavin, R. Gartner, C. Thornton, and R. Matsueda. Crime, Deterrence, and Rational Choice. *American Sociological Review*, 51(1):101–19, 1986.

[19] R. Sah. Social Osmosis and Patterns of Crime. *Journal of Political Economy*, 99(6):1271–1295, 1991.

[20] L. Saltzman, R. Paternoster, G. Waldo, and T. Chiricos. Deterrent and Experiential Effects:The Problem of Causal Order in Perceptual Deterrence Research. *Journal of Research in Crime and Delinquency*, 19:172–89, 1982.

[21] A. Schneider and L. Ervin. Specific Deterrence, Rational Choice, and Decision Heuristics: Applications in Juvenile Justice. *Social Science Quarterly*, 71(3):585–601, Sept. 1990.

[22] H. Tauchen, A. D. Witte, and H. Griesinger. Criminal Deterrence: Revisiting the Issue with a Birth Cohort. *Review of Economics and Statistics*, 76(3):399–412, Aug. 1994.

[23] W. Trumbull. Estimations of the Economic Model of Crime Using Aggregate and Individual Level Data. *Southern Economic Journal*, 94:423–39, 1989.

[24] W. K. Viscusi. The Risks and Rewards of Criminal Activity: A Comprehensive Test of Criminal Deterrence. *Journal of Labor Economics*, 4(3, pt. 1):317–40, 1986.

[25] W. K. Viscusi. *Rational Risk Policy.* Clarendon Press, Oxford, 1998.

[26] J. Waldfogel. Criminal Sentences as Endogenous Taxes: Are they 'Just' or 'Efficient'? *Journal of Law and Economics*, 36(1) pt.1:62–81, April 1993.

[27] J. Q. Wilson and G. Kelling. The Police and Neighborhood Safety: Broken Windows. *The Atlantic*, pages 29–38, March 1982.

[28] A. D. Witte. Estimating the Economic Model of Crime with Individual Data. *Quarterly Journal of Economics*, 94(1):57–84, Feb. 1980.

Figure 1: Distribution of Prior Beliefs for Three Types

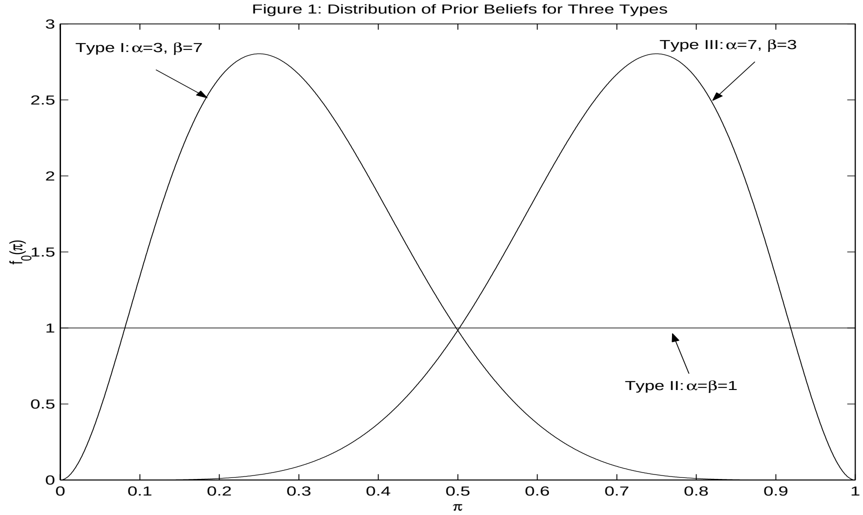

Figure 2: Simulated Crime Rates Over Time by Probability of Arrest (Type II Priors)

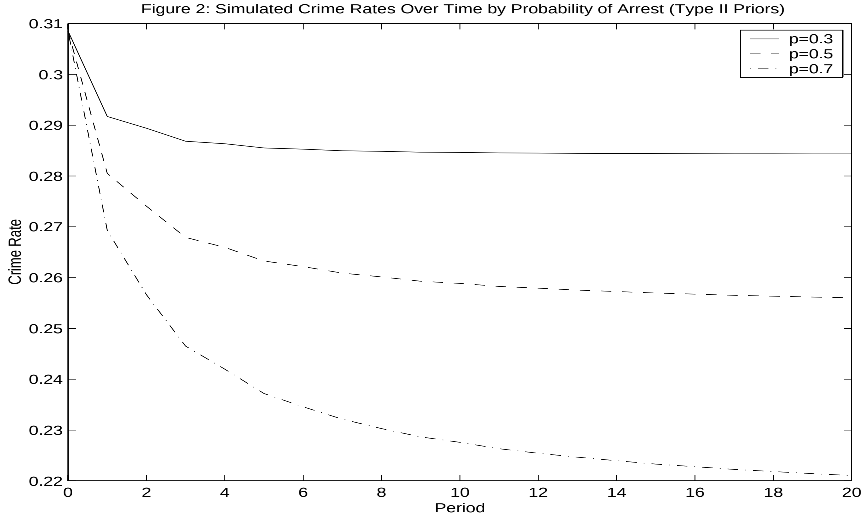

Figure 3: Simulated Crime Rates Over Time by Type

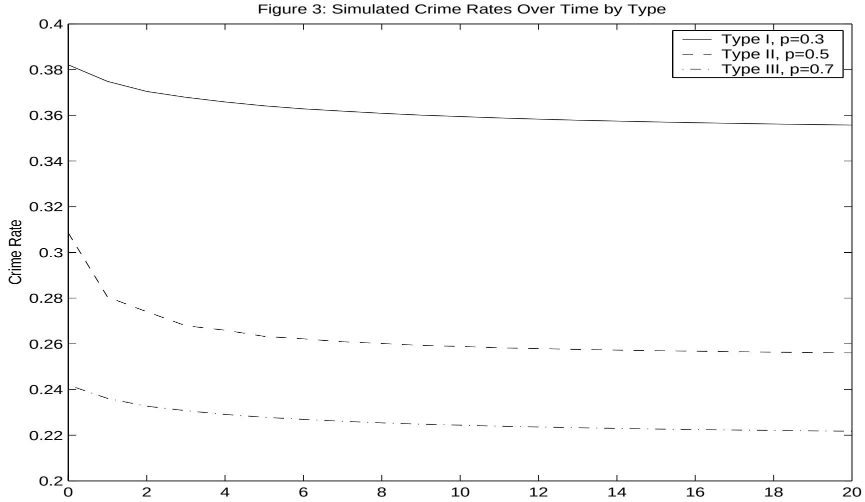

Figure 4: Average Perceived Arrest Probability over Time

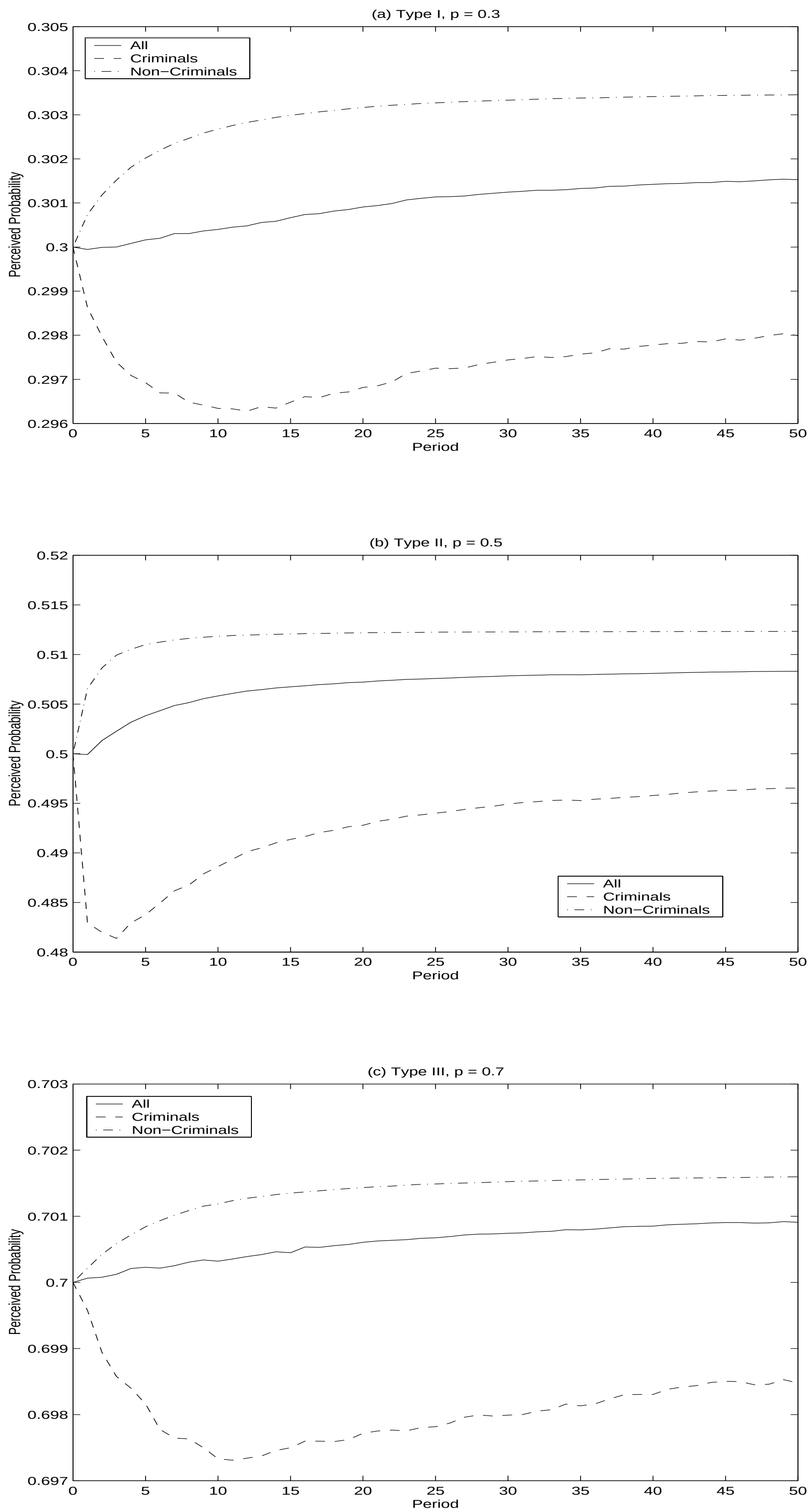

Figure 5: Average Perceived Probability of Arrest and Official Arrest Rate Over Time

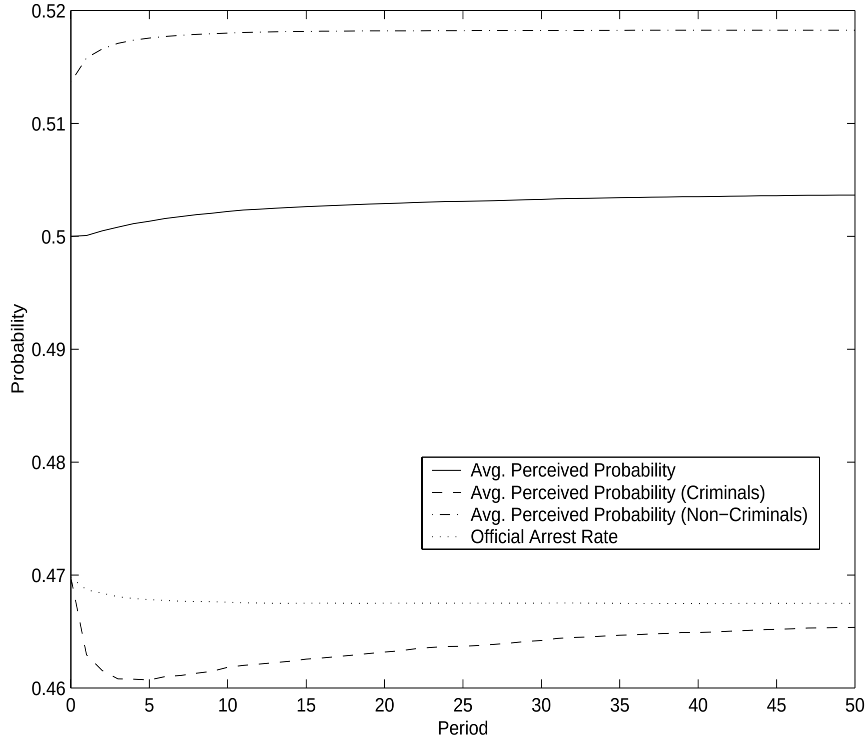

Figure 6: Simulated Crime Responses to Increases in p by Type

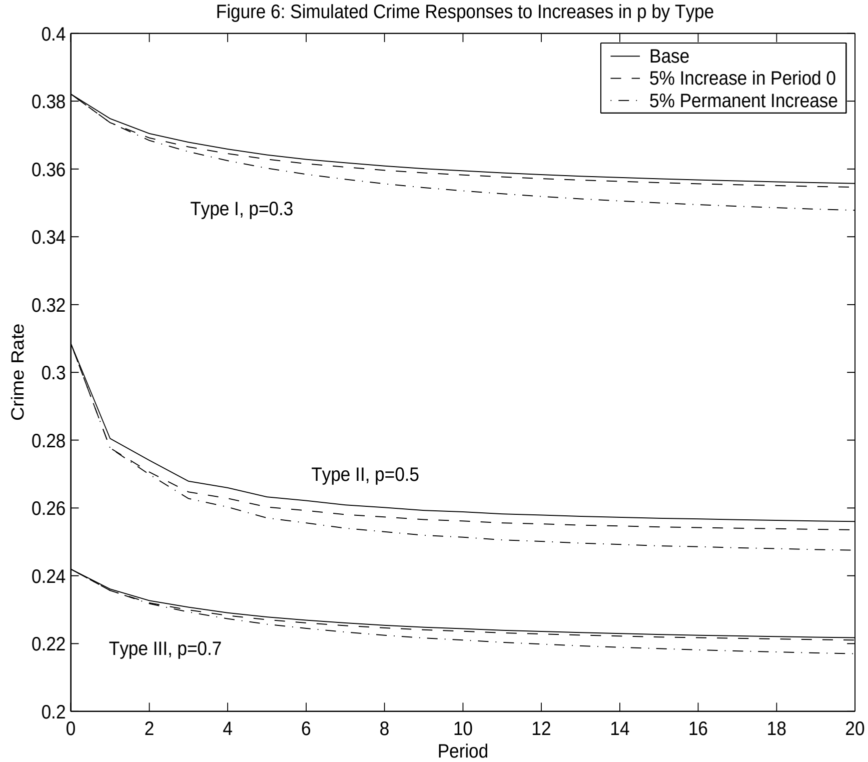

Figure 7: Distribution of Initial Perceived Probability of Arrest for Auto Theft (NLSY97, 1997)

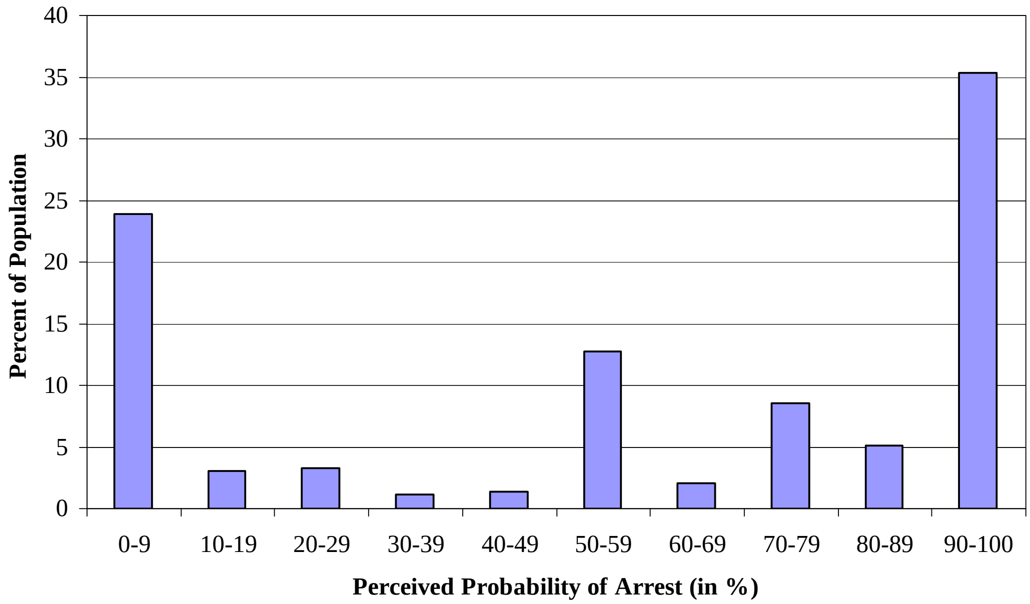

Figure 8: Changes in Perceived Probability of Arrest for Auto Theft from 1997 to 1998 (NLSY97)

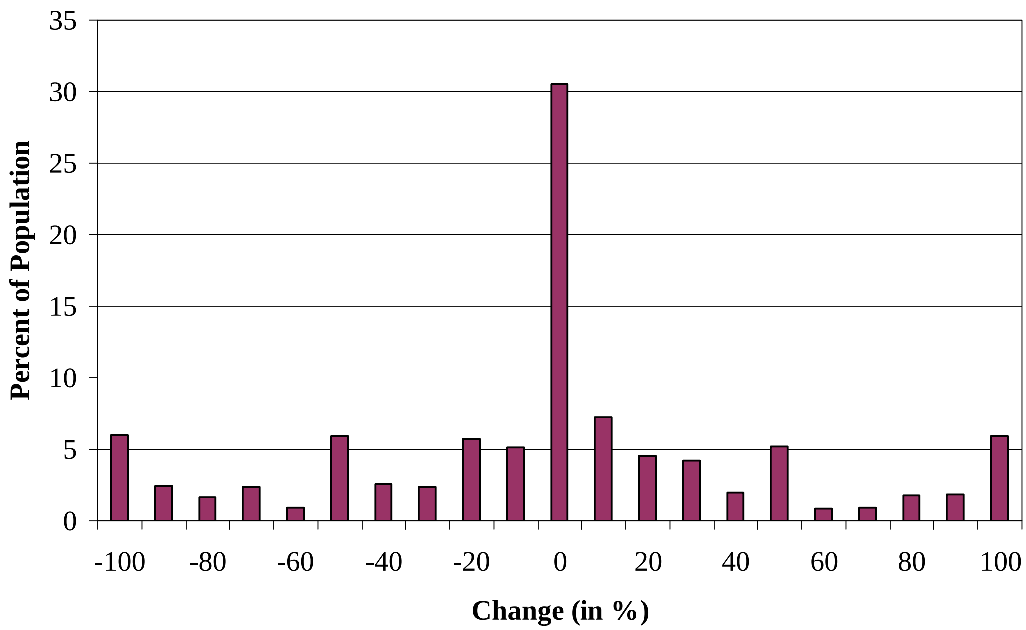

Figure 9: Distribution of Initial Perceived Probability (in %) of Arrest (NYS, 1983)

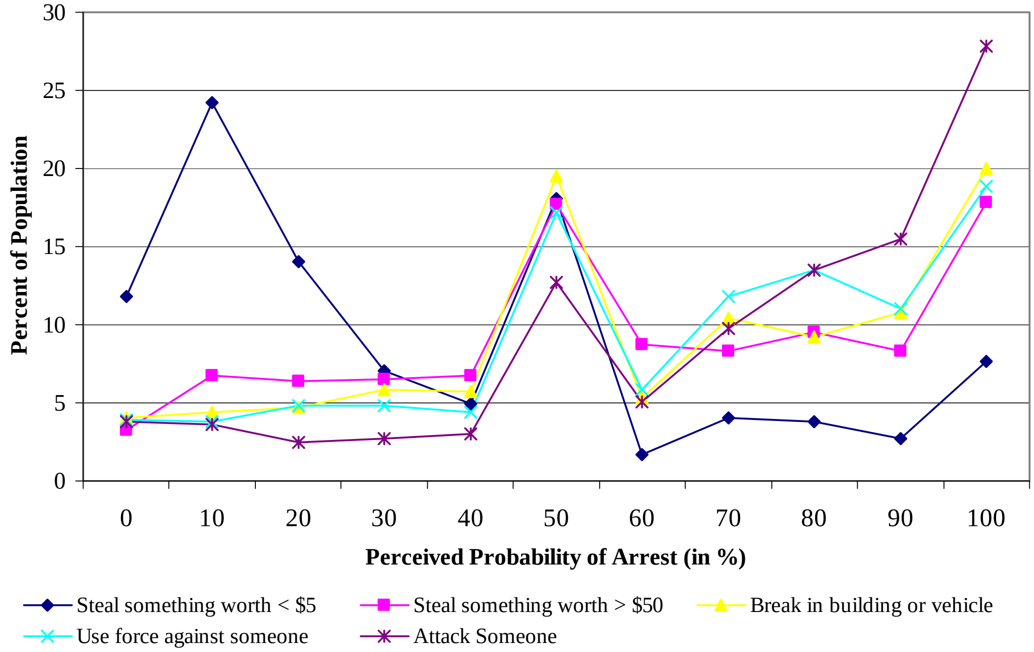

Figure 10: Changes in Perceived Probability (in %) of Arrest from 1983 to 1986 (NYS)

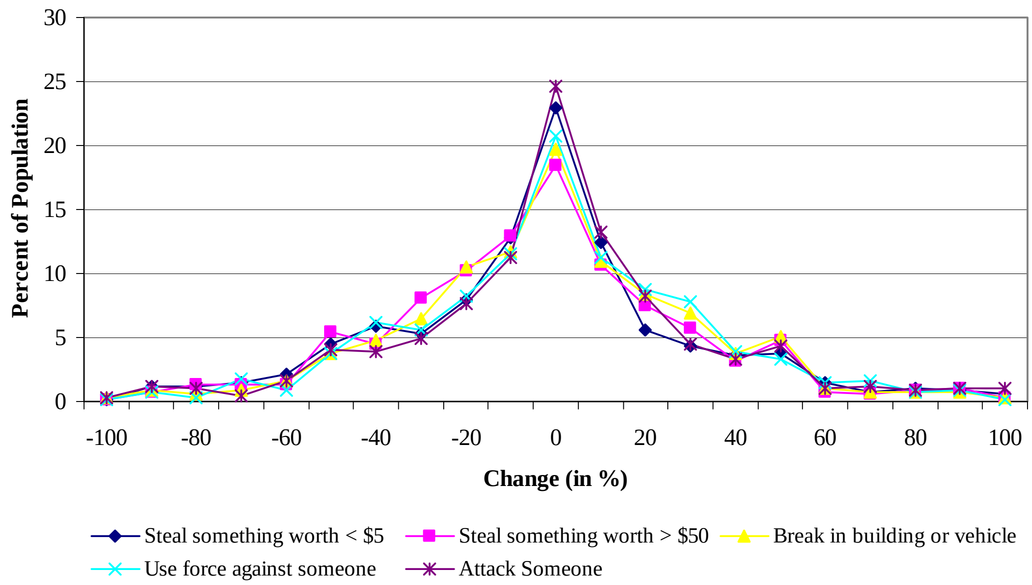

Table 1: Self-Reported Crime and Arrests as of 1997 (NLSY97)

	All	Blacks	Hispanics	Whites
Number of respondents	4310	1137	890	2166
Percent arrested for any offense	9.79	12.83	11.05	9.03
Percent arrested for theft	2.78	2.74	2.25	3.01
Percent who stole something	39.07	34.37	35.63	40.49
Percent who stole something worth > $50	10.17	10.46	10.26	9.85
Percent who stole a vehicle	1.73	1.77	2.03	1.71
Avg. number of thefts > $50 in the last year (of those who stole)	4.18	4.78	3.03	4.07
Avg. number of thefts > $50 in the last year	0.42	0.48	0.33	0.40
Persons arrested for theft / persons who stole	0.07	0.08	0.06	0.07
Persons arrested for theft / persons who stole > $50	0.27	0.26	0.22	0.31
Persons arrested for theft / persons who stole a vehicle	1.61	1.55	1.11	1.76
Arrests for theft / number of thefts > $50	0.07	0.07	0.07	0.09

Table 2: National Arrest Rates by Crime from the FBI's Uniform Crime Reports

Crime	Clearance Rate[1]	Arrests per Known Offense[2]	Reporting Rate[3]	Adjusted Arrest Rate[4]
1986				
Robbery	24.7	27.8	58.3	16.2
Assault	59.4	42.8	47.6	20.4
Burglary	13.6	14.1	52.3	7.4
Larceny-Theft	19.7	19.8	27.6	5.5
Motor Vehicle Theft	14.8	12.7	73.0	9.3
1997				
Robbery	26.3	27.5	55.8	15.4
Assault	58.5	53.2	43.7	23.2
Burglary	13.8	14.6	51.8	7.6
Larceny-Theft	19.8	19.5	27.9	5.4
Motor Vehicle Theft	14.0	12.5	79.8	10.0

Notes:

[1] An offense is 'cleared by arrest' when at least one person is arrested, charged with the crime, and turned over to the court for prosecution.

[2] Arrests per 100,000 inhabitants divided by known offenses per 100,000 inhabitants.

[3] Percent of crimes reported to police by the victim

[4] Arrests per known offense (column 2) adjusted for reporting rates (column 3).

Table 3: Mean Perceived Probabilities (in %) of Arrest for Auto Theft (NLSY97)

	All	Blacks	Hispanics	Whites
A) All Individuals	60.77	49.17	54.45	64.59
	(0.62)	(1.27)	(1.36)	(0.82)
B) Individuals who reported stealing	53.28	44.73	44.31	55.88
something worth more than $50	1.97	(3.82)	(4.18)	(2.68)
C) Individuals who reported stealing a car	49.66	47.00	33.71	49.59
	(4.06)	(9.50)	(8.22)	(5.61)
D) Weighted by number of thefts worth	40.62	37.39	39.29	44.12
more than $50	(2.23)	(13.88)	(16.96)	(6.65)

Standard errors in parentheses.

Table 4: OLS Estimates of Perceived Probability (in %) of Arrest for Auto Theft (NLSY97)

Variable	(1)	(2)	(3)
Intercept	78.617**	83.014**	68.226**
	(6.556)	(7.135)	(12.951)
age	-0.750*	-0.655	0.145
	(0.448)	(0.472)	(0.897)
black	-14.512**	-14.400**	-8.590**
	(1.710)	(1.823)	(3.060)
hispanic	-8.507**	-9.418**	-2.466
	(1.866)	(2.031)	(3.113)
living in MSA	-1.432	-2.466	-3.418
	(1.565)	(1.716)	(2.423)
living in South	-2.275	-3.618**	-6.221**
	(1.630)	(1.797)	(2.513)
living in Northeast	-6.578**	-9.106**	-10.777**
	(1.810)	(2.059)	(2.958)
living in West	-2.489	-3.824*	-5.625**
	(1.840)	(1.981)	(2.742)
State Probability of Arrest		-0.329**	-0.384**
		(0.127)	(0.175)
living with both parents			1.998
			(2.009)
family income (1000's of $)			0.000
			(0.024)
PIAT score (percentile)			0.100**
			(0.030)
mother a teenager at birth			-2.027
			(3.068)
gangs in neighborhood/school			-1.685
			(1.943)
R-square	0.027	0.030	0.033
Number of observations	4,022	3,585	1,754

* Significant at 0.10 level. ** Significant at 0.05 level.

Table 5: Self-Reported Crime and Arrests from 1984-1986 (NYS)

Percent black	16.45
Percent hispanic	4.25
Average number of arrests	0.17
Percent arrested	11.86
Percent arrested for a property offense[1]	1.14
Percent arrested for a violent offense[2]	0.71
Percent who stole something worth < $5	22.00
Percent who stole something worth > $50	4.00
Percent who broke into a building or vehicle	2.43
Percent using force to get money or things	0.71
Percent attacking someone to hurt or kill them	9.14

[1] Arrests for property offenses include various forms of theft, evading payment, burglary, breaking and entering, and dealing in stolen goods.

[2] Arrests for violent offenses include assault, robbery, and harassment.

Table 6: Mean Perceived Probabilities (in %) of Arrest (NYS 1983 & 1986)

Crime	All	Blacks	Hispanics	Whites
(i) Steal something worth $5 or less	33.84	43.55	38.37	31.86
	(0.79)	(2.20)	(4.21)	(0.85)
(ii) Steal something worth more than $50	57.81	63.10	58.57	56.78
	(0.76)	(2.09)	(4.36)	(0.84)
(iii) Break into a building or vehicle	62.49	67.22	66.33	61.54
	(0.76)	(2.06)	(4.22)	(0.83)
(iv) Use force to get money or things	64.55	64.57	66.33	64.41
	(0.74)	(2.04)	(4.51)	(0.81)
(v) Attack someone to hurt or kill them	72.00	72.12	70.61	72.08
	(0.73)	(2.11)	(4.76)	(0.78)
Sample Size	1468	245	49	1151

Standard errors in parentheses.

Table 7: Mean Perceived Probabilities (in %) of Arrest (NYS 1983 & 1986)

Crime	Did not commit this type of crime	Commited this type of crime	Weighted by Number of Crimes Committed
(i) Steal something worth $5 or less	35.64	19.19	35.97
(standard error)	0.85	(1.62)	(1.76)
[sample size]	[1307]	[161]	[161]
(ii) Steal something worth more than $50	57.94	53.00	46.55
(standard error)	(0.77)	(4.89)	(4.48)
[sample size]	[1428]	[40]	[40]
(iii) Break into a building or vehicle	62.77	51.67	44.67
(standard error)	(0.77)	(5.86)	(7.04)
[sample size]	[1432]	[36]	[36]
(iv) Use force to get money or things	64.50	56.25	60.83
(standard error)	(0.74)	(13.88)	(11.41)
[sample size]	[1455]	[8]	[8]
(v) Attack someone to hurt or kill them	73.43	54.78	52.76
(standard error)	(0.73)	(3.24)	(3.29)
[sample size]	[1355]	[113]	[113]

Standard errors in parentheses. Sample sizes in brackets.

Table 8: OLS Estimates of Perceived Probability (in %) of Arrest (NYS 1983)

Variable	(i) Steal something worth < $5	(ii) Steal something worth > $50	(iii) Break into building or vehicle	(iv) Use force against someone	(v) Attack Someone
Intercept	39.74**	99.68**	93.09**	80.18**	63.38**
	(13.15)	(12.83)	(12.76)	(12.55)	(12.63)
neighborhood crime	-1.15	-0.38	-1.36	-0.31	-2.55
	(2.59)	(2.52)	(2.51)	(2.47)	(2.49)
neighborhood disarray	-3.86	-1.75	-1.14	-1.51	2.18
	(3.04)	(2.97)	(2.95)	(2.90)	(2.92)
black	12.63**	8.28**	7.35*	3.42	2.89
	(3.95)	(3.85)	(3.83)	(3.76)	(3.79)
hispanic	8.16	3.85	5.16	0.47	-0.67
	(6.21)	(6.06)	(6.03)	(5.92)	(5.96)
poor	0.20	-3.21	-4.19	-3.10	-3.21
	(3.14)	(3.06)	(3.05)	(3.00)	(3.02)
living with both parents	-1.72	-4.23	-5.93**	-7.44**	-3.33
	(2.88)	(2.81)	(2.80)	(2.75)	(2.77)
mother graduate from HS	-1.63	1.95	-1.04	-1.34	2.27
	(2.80)	(2.73)	(2.72)	(2.67)	(2.69)
father graduate from HS	-2.21	-4.97*	-5.84**	-3.24	-5.51**
	(2.95)	(2.87)	(2.86)	(2.81)	(2.83)
age	-0.11	-1.77**	-1.06*	-0.39	0.59
	(0.60)	(0.58)	(0.58)	(0.57)	(0.57)
rural	5.49**	7.87**	5.88**	8.46**	5.55**
	(2.78)	(2.72)	(2.70)	(2.66)	(2.67)
central city	-2.11	-1.60	0.02	0.03	0.73
	(2.96)	(2.88)	(2.87)	(2.82)	(2.84)
R-square	0.0360	0.0463	0.0381	0.0331	0.0200
Number of observations	665	665	665	665	665

Standard errors in parentheses. * Significant at 0.10 level. ** Significant at 0.05 level.

Table 9: Belief Updating in the NLSY97
OLS Estimates of Perceived Probability (in %) of Arrest in 1998

Variable	(i)	(ii)
Intercept	18.86	18.83
	(12.90)	(12.87)
Steal something worth > $50 since 1997	-3.54	
	(4.00)	
Attack someone since 1997	-4.60	
	(2.57)	
Sell drugs since 1997	-10.96**	
	(3.53)	
number of times respondent		-0.21
stole something worth > $50 since 1997		(0.19)
number of times respondent		-0.52**
attacked someone since 1997		(0.20)
number of times respondent		-0.29**
sold drugs since 1997		(0.09)
perceived probability of arrest	0.21**	0.21**
for auto theft in 1997 (in %)	(0.02)	(0.02)
arrested since 1997	9.59**	
	(3.38)	
number of times arrested since 1997		4.05**
		(1.28)
black	-6.74**	-6.17**
	(2.61)	(2.60)
hispanic	-7.03**	-6.42**
	(2.70)	(2.70)
living with both parents	0.40	0.48
	(1.78)	(1.77)
mother a teenager at birth	-3.77	-3.72
	(2.74)	(2.74)
PIAT score (percentile)	0.10**	0.11**
	(0.03)	(0.03)
age	1.68**	1.61**
	(0.82)	(0.81)
living in South	1.63	1.32
	(2.21)	(2.20)
living in Northeast	1.61	1.69
	(2.56)	(2.56)
living in West	5.43**	5.22**
	(2.55)	(2.55)
living in MSA	-2.34	-2.08
	(2.10)	(2.10)
gangs in neighborhood/school	-0.88	-1.18
	(1.77)	(1.76)
R-square	0.0837	0.0862
Number of observations	2,207	2,206

Standard errors in parentheses. * Significant at 0.10 level. ** Significant at 0.05 level.

Table 10: Belief Updating in the NYS
OLS Estimates of Perceived Probability (in %) of Arrest in 1986

Variable	(i) Steal something worth < $5	(ii) Steal something worth > $50	(iii) Break into building or vehicle	(iv) Use force against someone	(v) Attack Someone
Intercept	43.87**	17.36	19.65	27.43*	43.42**
	(18.16)	(14.25)	(14.24)	(14.04)	(13.69)
commit respective crime in 1984 or 1985	-9.58**	-11.26*	-27.72**	-18.15	-20.46**
	(4.06)	(6.67)	(10.10)	(15.20)	(5.09)
perceived prob. of arrest in 1983 (in %)	0.32**	0.35**	0.39**	0.38**	0.29**
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
ever arrested since 1984	8.08**	5.83*	5.65	4.64	0.49
	(4.09)	(3.49)	(3.50)	(3.51)	(3.43)
black	6.53	0.77	0.03	-5.89	-4.93
	(4.65)	(3.67)	(3.70)	(3.66)	(3.61)
hispanic	-2.77	-3.95	0.47	4.59	0.08
	(8.18)	(6.12)	(6.17)	(6.10)	(6.03)
poor	4.35	7.08**	2.94	3.22	1.25
	(8.70)	(2.94)	(2.96)	(2.94)	(2.89)
living with both parents	-2.66	4.27	-2.10	0.75	2.32
	(3.45)	(2.77)	(2.79)	(2.77)	(2.72)
mother graduate from HS	-2.99	-4.72*	-2.36	-2.19	-4.83*
	(3.38)	(2.67)	(2.70)	(2.66)	(2.63)
father graduate from HS	-1.50	1.11	0.20	2.22	6.10**
	(3.49)	(2.79)	(2.80)	(2.77)	(2.74)
age	-0.89	0.55	0.75	0.43	0.27
	(0.73)	(0.55)	(0.55)	(0.55)	(0.54)
rural	2.63	3.54	3.56	-0.31	-1.57
	(4.17)	(3.02)	(30.32)	(3.00)	(2.97)
central city	-1.57	-0.12	1.74	0.78	-0.36
	(3.15)	(2.52)	(2.53)	(2.51)	(2.47)
R-square	0.1928	0.1643	0.1861	0.1597	0.1334
Number of observations	358	580	580	579	580

Standard errors in parentheses. * Significant at 0.10 level. ** Significant at 0.05 level.

Table 11: Belief Updating in the NYS
OLS Estimates of Perceived Probability (in %) of Arrest in 1986

Variable	(i) Steal something worth < $5	(ii) Steal something worth > $50	(iii) Break into building or vehicle	(iv) Use force against someone	(v) Attack Someone
Intercept	45.66**	18.78	20.56	28.29**	42.93**
	(18.22)	(14.22)	(14.15)	(13.96)	(13.63)
commit respective crime	-9.36**	-12.01*	-34.67**	-25.54	-21.44**
in 1984 or 1985	(4.20)	(6.90)	(10.59)	(15.99)	(5.10)
perceived prob. of arrest	0.32**	0.35**	0.39**	0.38**	0.29**
in 1983 (in %)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
arrested for a violent or	6.85	9.59	21.12**	15.58*	11.27
property crime since 1984	(8.47)	(8.32)	(8.46)	(8.43)	(7.93)
black	6.27	0.71	0.00	-5.92	-4.80
	(4.67)	(3.68)	(3.69)	(3.65)	(3.60)
hispanic	-2.73	-3.95	0.06	4.34	-0.20
	(8.23)	(6.13)	(6.15)	(6.09)	(6.02)
poor	3.90	6.79**	2.59	3.03	1.16
	(3.72)	(2.94)	(2.94)	(2.93)	(2.89)
living with both parents	-3.38	3.72	-2.61	0.35	2.33
	(3.44)	(2.75)	(2.76)	(2.74)	(2.70)
mother graduate from HS	-3.69	-4.88*	-2.31	-2.07	-4.52*
	(3.38)	(2.67)	(2.68)	(2.66)	(2.62)
father graduate from HS	-1.17	1.34	0.55	2.39	6.19**
	(3.51)	(2.79)	(2.79)	(2.77)	(2.74)
age	-0.89	0.53	0.73	0.41	0.26
	(0.73)	(0.55)	(0.55)	(0.55)	(0.54)
rural	2.46	3.41	3.42	-0.33	-1.49
	(4.19)	(3.02)	(3.02)	(3.00)	(2.96)
central city	-1.59	-0.10	1.89	0.83	-0.23
	(3.17)	(2.52)	(2.53)	(2.50)	(2.47)
R-square	0.1853	0.1621	0.1912	0.1622	0.1364
Number of observations	358	580	580	579	580

Standard errors in parentheses. * Significant at 0.10 level. ** Significant at 0.05 level.

Table 12: Mean Effect of a 10% Increase in the1997 Perceived Chance of Arrest for Auto Theft on Criminal Participation/Delinquency in 1998 (NLSY97)

Crime/Delinquency	Average Effect	Participation Rate	% Change in Participation
Auto Theft	-0.0007	0.0162	-4.46
Steal something worth < $50	-0.0052**	0.1605	-3.22
Steal something worth > $50	-0.0024**	0.0610	-3.87
Sell drugs	-0.0040**	0.0774	-5.17
Other property crime	-0.0017	0.0670	-2.59
Destroy property	-0.0056**	0.1833	-3.05
Attack or hurt someone	-0.0043**	0.1406	-3.08
Smoke marajuana	-0.0033	0.1929	-1.70
Smoke cigarettes	-0.0042*	0.3421	-1.22
Drink alcohol	-0.0032	0.4525	-0.71

Note: All probits control for age and age-squared, race/ethnicity (black and hispanic), residence in an MSA, living with both natural parents, teenage mother, PIAT math scores, region of residence, and whether there are gangs in the neighborhood or school.

* Significant at 0.10 level. ** Significant at 0.05 level.

Table 13: Probit Estimates of Criminal Participation in 1984-86 (NYS)

Variable	(i) Steal something worth < $5	(ii) Steal something worth > $50	(iii) Break into building or vehicle	(iv) Use force against someone	(v) Attack Someone
Intercept	2.228**	-0.445	1.670	-0.446	0.936
	(0.850)	(1.168)	(1.486)	(2.159)	(0.867)
perceived prob. of arrest	-0.008**	-0.001	-0.008*	-0.004	-0.008**
reported in 1983 (in %)	(0.003)	(0.004)	(0.005)	(0.007)	(0.002)
black	-0.369	-0.345	-0.231	-	-0.091
	(0.288)	(0.380)	(0.451)	-	(0.250)
hispanic	-0.537	-0.116	-	-	-0.824
	(0.529)	(0.493)	-	-	(0.569)
poor	0.042	0.040	0.072	0.288	0.322*
	(0.205)	(0.263)	(0.301)	(0.405)	(0.188)
living with both parents	0.081	-0.295	-0.255	-0.415	-0.038
	(0.190)	(0.235)	(0.283)	(0.412)	(0.185)
mother graduate from HS	-0.071	-0.455*	-0.562*	-0.252	-0.172
	(0.182)	(0.238)	(0.292)	(0.441)	(0.179)
father graduate from HS	0.171	0.038	-0.033	-0.129	-0.177
	(0.194)	(0.258)	(0.303)	(0.434)	(0.188)
age	-0.130**	-0.031	-0.121*	-0.068	-0.078**
	(0.039)	(0.053)	(0.068)	(0.101)	(0.040)
rural	-0.614**	-0.944**	-0.706*	-	-0.005
	(0.212)	(0.410)	(0.409)	-	(0.188)
central city	-0.111	0.162	-0.151	-	0.238
	(0.176)	(0.222)	(0.286)	-	(0.190)
Log Likelihood	-183.0480	-88.3795	-57.8474	-22.0760	-165.8838
Number of observations	380	582	582	582	582

Standard errors in parentheses. * Significant at 0.10 level. ** Significant at 0.05 level.

Table 14: Mean Effect of a 10% Increase in Perceived Chance of Arrest (1983) on Criminal Participation in 1986 (NYS)

Crime/Delinquency	Average Effect	Participation Rate	% Change in Participation
(i) Steal something worth $5 or less	-0.0207**	0.220	-9.43
(ii) Steal something worth more than $50	-0.0012	0.040	-2.96
(iii) Break into a building or vehicle	-0.0044*	0.024	-18.11
(iv) Use force to get money or things	-0.0007	0.007	-9.72
(v) Attack someone to hurt or kill them	-0.0120**	0.091	-13.08

Note: See Table 13 for other regressors and coefficient estimates. Effects are for a 10% change in the perceived probability of arrest for the respective crime.
* Significant at 0.10 level. ** Significant at 0.05 level.

Table A-1: Mean Perceived Probability (in %) of Punishment (if Arrested for Auto Theft) (NLSY97)

	All	Blacks	Hispanics	Whites
A) All individuals				
(ii) Prob. of release w/o charge if arrested	29.69	32.90	32.00	28.58
	(0.51)	(1.08)	(1.14)	(0.69)
(iii) Prob. of fine & release if arrested	52.47	49.52	55.26	52.64
	(0.55)	(1.13)	(1.22)	(0.74)
(iv) Prob. of jail term if arrested	45.84	44.70	50.67	45.71
	(0.57)	(1.15)	(1.24)	(0.78)
B) Individuals who reported stealing something worth more than $50				
(i) Prob. of release w/o charge if arrested	26.68	27.41	32.89	26.43
	(1.67)	(3.17)	(4.01)	(2.32)
(ii) Prob. of fine & release if arrested	47.60	46.04	48.17	47.07
	(1.91)	(3.86)	(4.09)	(2.62)
(iii) Prob. of jail term if arrested	46.28	48.86	46.42	46.56
	(1.92)	(3.79)	(4.05)	(2.68)
C) Individuals who reported stealing a car				
(i) Prob. of release w/o charge if arrested	30.98	27.33	34.12	32.38
	(4.07)	(8.13)	(10.29)	(5.78)
(ii) Prob. of fine & release if arrested	38.88	29.44	48.00	39.85
	(4.16)	(8.92)	(10.90)	(5.66)
(iii) Prob. of jail term if arrested	46.74	50.11	42.82	46.44
	(4.58)	(9.39)	(9.97)	(6.39)
D) Weighted by number of thefts worth more than $50				
(i) Prob. of release w/o charge if arrested	31.56	22.60	47.33	24.85
	(2.12)	(10.38)	(19.05)	(5.51)
(ii) Prob. of fine & release if arrested	43.29	50.56	42.80	40.47
	(2.31)	(14.73)	(17.02)	(7.03)
(iii) Prob. of jail term if arrested	48.13	34.29	61.82	44.53
	(2.28)	(13.26)	(14.97)	(7.33)

Standard errors in parentheses.

Table A-2: OLS Estimates of Perceived Probability (in %) of Punishment for Auto Theft (NLSY97)

Variable	(i) Prob. of release w/o charge if arrested	(ii) Prob. of fine & release if arrested	(iii) Prob. of jail term if arrested
Intercept	32.768**	49.928**	56.356**
	(10.099)	(10.711)	(11.165)
age	-0.094	0.377	-0.200
	(0.717)	(0.761)	(0.793)
black	2.752	-0.942	-5.064*
	(2.382)	(2.526)	(2.633)
hispanic	4.454*	6.174**	2.236
	(2.448)	(2.596)	(2.706)
living in MSA	0.018	-2.230	-2.444
	(1.844)	(1.956)	(2.039)
living with both parents	-2.252	1.677	0.370
	(1.606)	(1.703)	1.775
family income (1000's of $)	-0.011	-0.038*	-0.042*
	(0.020)	(0.021)	(0.022)
PIAT score (percentile)	-0.007	0.047*	-0.035
	(0.024)	(0.025)	(0.027)
mother a teenager at birth	-3.455	-3.838	-1.627
	(2.447)	(2.596)	(2.705)
gangs in neighborhood/school	0.470	-1.905	0.257
	(1.541)	(1.634)	(1.703)
living in South	1.713	-1.748	0.637
	(1.933)	(2.050)	(2.137)
living in Northeast	1.873	-2.787	-5.690**
	(2.231)	(2.366)	(2.466)
living in West	-3.124	-2.208	4.157*
	(2.173)	(2.305)	(2.403)
R-square	0.009	0.011	0.015
Number of observations	1947	1947	1947

Standard errors in parentheses. * Significant at 0.10 level. ** Significant at 0.05 level.