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INDIVIDUAL PERCEPTIONS OF THE CRIMINAL JUSTICE SYSTEM

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ABSTRACT

This paper empirically 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. While beliefs about the probability of an arrest are positively correlated with local official arrest rates, they are largely idiosyncratic and unresponsive to information about the arrests of other random individuals and local neighborhood conditions. There is little support, therefore, for the `broken windows' theory of Wilson and Kelling (1982). Yet, perceptions do respond to changes in an individual's own criminal and arrest history. 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. Beliefs respond similarly to changes in a sibling's criminal and arrest history. The perceived probability of arrest is then linked to subsequent criminal behavior. Cross-sectionally, youth with a lower perceived probability of arrest are significantly more likely to engage in crime during subsequent periods. Following an arrest, individuals commit less crime, consistent with deterrence theory and the fact that their perceived probability of arrest increases.

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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. This paper uses self-reported beliefs about the probability of arrest from longitudinal data to examine the empirical relationship between the perceived probability of arrest and subsequent criminal activity.

We also show 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 while avoiding arrest reduce their perceived probability of arrest, while those who are arrested increase their perceived probability.[3] Beliefs also respond to changes in the criminal and arrest histories of their siblings, but not to information about other random persons.

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 outlines a complementary framework for analyzing how an individual's own crime and arrest history affects his beliefs and how those beliefs affect behavior.[4] 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 different points in their criminal careers). In Sah's model and the framework discussed in this paper, there are delayed responses in criminal activity when official arrest rates increase. Furthermore, even a temporary increase in arrest rates can have long-term impacts on crime rates. The significance of these results depends on the relevance of and information used in belief updating. While a few empirical studies[5] have found that time patterns in

[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 – an important contribution of this paper.

[4]This framework is developed more formally and fully analyzed in Lochner (2002).

[5]Taking a VAR approach to estimating the relationship between crime, arrests, and the business cycle, Corman, Joyce, and Lovitch (1987) find empirical evidence for both delayed effects of an increase in arrests on crime and for long-term effects of a temporary increase in arrests. Ayres and Levitt (1998) find evidence consistent with learning among auto thieves when Lojack (a new technology allowing police to locate stolen vehicles equipped with the system) is introduced

crime and arrests are consistent with information transmission and belief updating among criminals, this paper directly examines the empirical importance of individual (and sibling) crime and arrest histories as well as alternative sources of information in determining beliefs about the probability of arrest.

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. Furthermore, Heavner and Lochner (2001) show that policies like anti-gang initiatives or mentor programs will have heterogeneous impacts on neighborhoods that differ in the current level of gang and criminal activity. More generally, the way in which individuals acquire information and develop expectations is important in determining outcomes and policy effects in any environment; yet, little is actually known about these processes.[6]

After a brief discussion of the main issues involved in studying the evolution of beliefs about the probability of arrest and criminal behavior in Section 2, this paper empirically examines these issues using data from the NLSY97 and NYS. Section 3 summarizes the data on criminal participation and perceptions in the NLSY97 and NYS, exploring how beliefs vary in a population of young males. The role of belief updating is examined in Section 4, and the influence of beliefs about the probability of arrest on criminal activity is discussed in Section 5. Section 6 concludes.

2 The Evolution of Crime and Beliefs

This section outlines a framework for thinking about the interaction of beliefs about the probability of arrest and criminal behavior. The primary goal is to provide intuition about the important issues involved in the empirical study below rather than a rigorous theoretical treatment of the problem.[7]

to some cities.

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

[7]For a more complete theoretical analysis, see Lochner (2002).

We also discuss a few policy implications that underscore the potential importance of belief updating in determining criminal decisions over the lifecycle.

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

First, consider the decision to commit crime when there is uncertainty about the probability of arrest. Following Becker (1968), assume that individuals choose to commit crime if the expected benefits exceed the expected costs. For simplicity, assume the benefits to each individual i from committing a crime at age t, B_{it}, are known beforehand. Individuals also know the punishment, $J_{it} \geq 0$, associated with an arrest, but they do not necessarily know their own probability of arrest. Instead, they have some beliefs about that probability (π_i). Let the cumulative distribution function $F(\pi|H_i^t)$ represent an individual's perceived distribution of his own arrest probability conditional on information available to him at date t, H_i^t. Assuming no intertemporal effects of arrest or criminal behavior (except through beliefs), individual i will commit crime in period t if and only if

$$B_{it} > J_{it} \int_0^1 \pi dF(\pi|H_i^t).$$

For simplicity, this decision rule ignores any incentive to commit crime in order to learn more about the true probability. In this sense, individuals behave myopically each period.[8] Defining the benefit-cost ratio, $R_{it} = B_{it}/J_{it}$, yields the following decision rule for crime:

$$\text{commit crime if and only if} \qquad E(\pi|H_i^t) < R_{it}, \tag{1}$$

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

Now, consider the evolution of beliefs. Assume that initial beliefs about the probability of arrest are given by $F_0(\pi)$ (where $F_0(0) = 0$ and $F_0(1) = 1$, reflecting the fact that π is itself a probability). Any

[8]Incorporating this type of strategic behavior is straightforward and would create an additional incentive to engage in crime when beliefs are uncertain.

number of assumptions can be made about how individuals update their beliefs given new information as well as what types of information are relevant for belief updating. Since the criminal decision rule in equation (1) depends on the expectation of the probability of arrest, $E(\pi|H_i^t)$, we consider how this measure of beliefs evolves.

Beliefs about the probability of arrest are likely to depend on an individual's own (past) criminal behavior and arrest outcomes, the criminal and arrest outcomes of others around him, and more general signals that may come from local arrest rates or neighborhood conditions.[9] Let c_{it} be an indicator equal to one if individual i commits a crime in period t and zero otherwise. Similarly, let A_{it} be an indicator equal to one if he is arrested in period t and zero otherwise. Let $\tilde{c}_{it}$ and $\tilde{A}_{it}$ represent vectors of these indicators for individuals that person i associates with. Finally, we denote any new information about the local environment by Z_{it}. Information accumulates according to $H_i^t = (H_i^{t-1}, c_{i,t-1}, A_{i,t-1}, \tilde{c}_{i,t-1}, \tilde{A}_{i,t-1}, Z_{i,t-1})$. A fairly general rule for updating beliefs[10] is given by

$$E(\pi|H_i^t) = g(E(\pi|H_i^{t-1}), c_{i,t-1}, A_{i,t-1}, \tilde{c}_{i,t-1}, \tilde{A}_{i,t-1}, Z_{i,t-1}). \tag{2}$$

One might reasonably assume that the expected probability of arrest is increasing in the previous expected probability ($g_1 \geq 0$).[11] The expected probability of arrest should be decreasing in the number of crimes committed (by oneself or others) holding the number of arrests constant ($g_2 \leq 0$ and $g_4 \leq 0$). It also seems reasonable to assume that the total effect of committing a crime and getting arrested for it should lead to an increase in the expected probability of arrest (i.e. $g_2 + g_3 \geq 0$ and $g_4 + g_5 \geq 0$). One would also expect beliefs to be increasing in measures of the official local arrest rate. Furthermore, the 'broken windows' theory of Wilson and Kelling (1982) suggests that individuals are likely to think the probability of arrest is lower in communities in which buildings are rundown, windows are broken, and lawlessness is rampant. An important contribution of this paper will be an empirical examination of these assumptions.

These basic assumptions about $g(\cdot)$ generate a number of interesting implications for lifecycle criminal behavior and the evolution of beliefs. As an example, consider an individual who elects to commit a crime. If he avoids arrest, he will unambiguously lower his perceived probability of arrest (assuming no changes in other information). This will raise the likelihood that he commits crime the

[9] By focusing only on information received from others, Sah (1991) neglects the important role that an individual's own criminal and arrest history plays in shaping his own beliefs and, therefore, subsequent criminal decisions. The true probability of arrest is, most probably, quite heterogeneous across individuals. If this type of heterogeneity is substantial, it may imply that information acquired from others plays little role in the development of an individual's beliefs about the probability that he himself will be arrested. Instead, his own history would be the primary determinant.

[10] A more general rule would allow $E(\pi|H_i^t)$ to depend on the entire distribution of prior beliefs, $F(\pi|H_i^{t-1})$, rather than just $E(\pi|H_i^{t-1})$.

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

following period. On the other hand, if he is arrested, he should raise his expected probability of arrest, making him less likely to commit crime in the future. Thus, criminal profiles will be determined, in part, by the randomness associated with an arrest. The 'lucky' individual who manages to avoid an arrest early on is more likely to continue committing crime thereafter than is the 'unlucky' person who gets arrested. Following the same line of argument, individuals with 'lucky' older siblings who engage in crime and get away with it are more likely to engage in crime themselves.

Much more can be said about the evolution of beliefs and crime if we are willing to make stronger assumptions about the structure of information and updating. For example, consider Bayesian decisionmakers who only acquire information about the probability of arrest from their own criminal and arrest histories.[12] They will update their beliefs as follows:

$$E(\pi|H_i^t) = E(\pi|H_i^{t-1}) - \left[\frac{V(\pi|H_i^{t-1})}{1-E(\pi|H_i^{t-1})}\right] c_{i,t-1} + \left[\frac{V(\pi|H_i^{t-1})}{E(\pi|H_i^{t-1})(1-E(\pi|H_i^{t-1}))}\right] c_{i,t-1} A_{i,t-1}, \quad (3)$$

where $V(\pi|H_i^{t-1}) = E(\pi^2|H_i^{t-1}) - \left[E(\pi|H_i^{t-1})\right]^2$ is the variance of beliefs about the probability of arrest given history H_i^{t-1}.

Those not committing crime will not change their beliefs, but those choosing to commit a crime will update their beliefs depending on whether or not they are arrested. The expected probability of arrest increases among those who are arrested, while it decreases among those who are not. The magnitude of the change depends on both the variance and mean of the belief distribution. When there is a lot of uncertainty (i.e. $V(\pi|H_i^{t-1})$ 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). This variance is likely to be particularly high early in an individual's life, while it should decline as an individual acquires more and more information. This implies that the beliefs of young criminals should respond more to an arrest than should the beliefs of veteran criminals. Additionally, individuals should learn quickly about the probability of arrest for crimes that are committed frequently. At any given age, then, individuals should respond less to new information about the probability of arrest for these crimes.

The responsiveness to an arrest or non-arrest also depends on the previous expected probability of arrest. When this expected probability ($E(\pi|H_i^{t-1})$) is high, individuals will show little response to an arrest while they will substantially reduce their expected probability if they avoid an arrest. On the other hand, when the expected probability of an arrest is low, individuals that are arrested will substantially revise their probability of arrest upward, while those that are not will revise their

[12] Alternatively, individuals may receive information from other sources, but it may be largely irrelevant due to the idiosyncratic nature of criminal ability.

expected probability downward by much less. Current beliefs, therefore, determine the importance of new information.

In this environment, there is no reason to think that beliefs will be accurate. Criminals are likely to be optimistic in that they will tend to believe that their probability of arrest is lower than it actually is, while non-criminals will tend to be pessimistic about their chances of evading arrest. This is even true among those who start their criminal careers with unbiased prior beliefs. To understand why, suppose that all individuals begin with unbiased priors. Any change in beliefs, therefore, leads to a bias. Since individuals only commit crime if the expected probability is low enough, those who continue to engage in crime tend to be the lucky ones who have not been arrested for their past crimes. On average, they reduce their perceived probability of arrest leading to a systematic downward bias. At the other extreme, those choosing not to commit crime are likely to have started out with a very high perceived probability of arrest or to have experienced an arrest sometime in the past causing them to revise their beliefs upwards. The latter subgroup of current non-criminals (but former criminals) will bias the average beliefs of all non-criminals upwards. With homogeneity in the true probability of arrest and unbiased prior beliefs, we would expect that, on average, criminals under-estimate the official arrest rate while non-criminals over-estimate the official arrest rate. Beliefs in the entire population should be relatively accurate; though, there may be some bias.

When there is heterogeneity in the true probability of arrest across individuals, average beliefs about the probability of arrest will tend to be higher than official arrest rates even if prior beliefs are unbiased for each individual. This is because those with high true probabilities (and, therefore, high prior beliefs about the probability) will not engage in crime. The opposite is true for those with low true and perceived probabilities. Official arrest rates will be lower than the average true probability across all individuals, since they only reflect the probability of arrest for those choosing to commit a crime. The biases in beliefs discussed earlier will arise among non-criminals and criminals, but the overall average belief about the probability of arrest will generally be higher than the official arrest rate due to selection into criminality. The greater the heterogeneity in true probabilities, the greater will be the difference between average beliefs and official arrest rates.

If we continue to assume that individual beliefs only depend on policy-invariant priors and individual crime and arrest histories so $g_6 = 0$ (e.g. individuals either do not hear about policy changes or do not believe such announcements), then two policy implications contrast sharply with those predicted by standard models that assume the true probability of arrest is known with certainty. First, an increase in the true probability of arrest (e.g. an increase in the number of police or more lax rules on police searches) will have no immediate effect on crime, but it will have lagged effects. This is true of both permanent and temporary changes. Policy affects are lagged because they only affect crime indirectly through beliefs, which take time to evolve. Each additional arrest that occurs as a result of the increased true probability of arrest will cause the affected criminal to revise his perceived probability of arrest upwards. This increases the likelihood that he refrains from committing further crimes in the future. Even with a direct announcement effect on beliefs, the long-run effects of an increase in the probability of arrest would be greater than the short-run effects. On the other hand, when the probability of arrest is known with certainty, all effects on crime would be immediate and would only continue as long as actual arrest rates remain high.[13]

Second, changes in the true probability of arrest should not only affect the level of crime, but they should also affect the age-crime profile as criminals slowly learn about any changes through experience. To the extent that initial criminal decisions only depend on prior beliefs and tastes, there will be no impact of an increase in the true probability of arrest on the initial crime rate of a cohort. But, subsequent crime rates will decline as more and more individuals experience an arrest. Overall, crime should decline more quickly with age (at least initially). With direct announcement effects on initial beliefs, crime rates would also decline among youth, offsetting some of the learning effect. This learning effect is entirely absent in standard models with fully-informed agents.

Summarizing, this framework suggests 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. Additionally, it explains why criminals may be optimistic about their chances of evading arrest when non-criminals are pessimistic. It also suggests that the average perceived probability of arrest is likely to be greater than official arrest rates even when prior beliefs are unbiased. The importance of these effects will depend on the information acquired by individuals as well as the process by which they update their beliefs. In the following sections, we empirically examine these issues.

3 Crime and Perceptions

Crime and Beliefs in the NLSY97

The NLSY97 contains a sample of 9,022 individuals (4,621 males) ages 12-16 in 1997. While the annual survey is ongoing, only a panel for 1997-2000 is currently available. Information relevant to this study includes data on family background, individual achievement test scores, neighborhood characteristics,

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

criminal behavior, and perceptions about the probability of arrest and various punishments for auto theft.[14]

The extent of criminal activity among young males in the NLSY97 is shown in Table 1. About 5.5% of young males report committing a theft of over $50 in any given year, with blacks reporting the most involvement and whites the least. Slightly more than 1% of the sample reports committing auto theft. Approximately 8% of all young males report an arrest for some offense in any year, and only 1.6% report an arrest for theft.

Unfortunately, the data do not allow us to determine what category or type of theft for which an arrest was made. To the extent that most arrests occur for thefts of something worth more than $50, we can approximate the arrest rate for theft by race/ethnicity. Between 0.25 (hispanics) and 0.33 (blacks) 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 0.04 for hispanics to 0.06 for blacks and whites. According to these figures, less than one out of every ten thefts of greater than $50 results in an arrest, and minorities are no more 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 among those choosing to steal.

While these rates are substantially lower than official clearance rates[15] for burglary, larceny-theft, and motor-vehicle theft, they accurately reflect official arrest rates for theft after adjusting for non-reporting (to the police) by victims. Adjusted arrest rates for theft are lowest for the general larceny-theft category (5.4%), slightly higher for burglary (7.6%), and highest for motor vehicle theft (10.0%).[16] Thus, arrest rates for theft among youth surveyed by the NLSY97 closely correspond to official na-

[14] 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]?"

[15] 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.

[16] 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.

tionwide 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 beliefs about the likelihood of arrest, it is, therefore, important to consider individual characteristics which might be correlated with criminal abilities as well as those which may affect opinions about law enforcement. Figure 1 shows the kernel density estimated (using a biweight kernel with a bandwidth of 5) distribution of the perceived probability of arrest for auto theft among young males in the NLSY97. Most youth report much higher perceived probabilities of arrest than is reflected in national arrest rates or in the actual arrest rates for thefts committed by this sample.[17] The figure shows strong focal points at probabilities of 0, 0.5, 0.75, 0.9, and 1.

Young males from all racial and ethnic backgrounds tend to report a relatively high probability of arrest as shown in Table 2. While most previous research has shown that official arrest rates do not vary across races (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 here.[18] Panel (A) of the table shows that both young black (52%) and hispanic (54%) males tend to have significantly *lower* perceived probabilities of arrest for auto theft than the average young white male (64%).

The fact that perceived probabilities of arrest are substantially higher than true arrest rates does not necessarily imply that individuals over-estimate their own probability of arrest. As noted earlier, 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 young males engaged in crime report fairly high probabilities of arrest. Panel (B) of Table 2 reveals probabilities for young males who reported stealing something worth more than $50 in the previous year; panel (C) shows perceptions for young males who committed auto theft; and panel (D) calculates average perceived probabilities using the number of thefts of over $50 committed in the last year by each individual to weight the observations. Panel (D) accounts for the possibility that individuals who commit the most crime also hold the lowest perceived probabilities of arrest. If each individual's perceived probability is correct, the weighted average of all perceived probabilities for arrest in panel (D) should equal the sample arrest rate.

Among teenage males who have stolen something worth more than $50, whites believe that their

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

[18] 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.

probability of facing arrest is about 10% higher than hispanics or blacks. Among auto thieves, the gap between whites and the two minorities is around 7%. Weighting beliefs by the number of thefts suggests a gap of about 6%. There is little evidence to support the proposition that young 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. As discussed in the previous section, these differences in beliefs can be attributed to at least two 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, and (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. It is also the case that 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'; however, there is little reason to expect that this should bias beliefs in one direction or the other. Given the first factor, it is surprising that even those engaged in auto theft report an average expected arrest rate of 40-50%.

An obvious explanation for the discrepancy in beliefs and true arrest rates is that individuals misinterpret the question.[19] 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 (30% 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 impossible to know for sure how people interpret and answer these questions. To the extent that these measures of beliefs change in response to new information and affect behavior in economically interesting ways, it seems likely that they contain important (if noisy) information about true beliefs. Ultimately, this is an empirical question, which we explore in detail.

Table 3 uses ordinary least squares (OLS) regression to examine the importance of county-level arrest rates, individual characteristics, family background, and geographic variables in explaining the perceived probability of arrest for auto theft. While the reported results are based on the entire sample of NLSY97 respondents, the results are very similar when restricted to those reporting a theft of something worth more than $50 sometime in the previous year. Column (i) examines the

[19]However, examining responses to a variety of questions about the probability of different events occurring in the near future, Walker (2000) finds little evidence that NLSY97 youth are unable to grasp the concept of probability.

relationship between county arrest rates for motor vehicle theft[20] and the perceived probability of arrest. The estimates suggest a positive correlation with a coefficient of 0.13. Column (ii) adds demographic indicators for age and race. The coefficient on local arrest rates drops by half, suggesting that much of the correlation between beliefs and official arrest rates is due to locational differences in demographics that are correlated with beliefs. Column (iii) adds an indicator for current residence in a Metropolitan Statistical Area (MSA). The effects of county arrest rates decline further, but MSA status is statistically important. Young males living in an MSA believe they are less likely to be arrested, consistent with lower official arrest rates in urban communities. To the extent that most of the true variation in arrest rates across communities depends on metropolitan status and the demographic characteristics of a neighborhood, it is not surprising that the correlation between beliefs and official county arrest rates, which are undoubtedly measured with error, disappears after controlling for these factors.

Given the theory discussed in Section 2, one might expect that older individuals are better informed about the true arrest rate than are younger respondents. However, the results from including interactions between MSA status and age as well as county arrest rates and age in the regressions of Table 3 do not support this conclusion. Coefficient estimates for these interactions are always insignificantly different from zero. On average, beliefs do not more accurately reflect official arrest rates among older individuals.

Column (iv) of Table 3 adds detailed family background measures (specifically, low current family income, whether the respondent lived with both his natural parents in 1997, whether his mother was a teenager at birth) and math achievement test scores.[21] This has little effect on the estimates already discussed. Young black and hispanic males report a lower probability of arrest than white males even after controlling for age, local arrest rates, residence in a MSA, and other family background measures. However, racial differences are considerably smaller than their unconditional counterparts shown in panel (A) of Table 2. Perhaps surprisingly, family background has little affect on reported beliefs about the probability of arrest. Other than race/ethnicity, only the effects of Peabody Individual Achievement Test (PIAT) scores for math are statistically significant. In contrast to an 'ability to

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

[21]Peabody Individual Achievement Test (PIAT) scores for math are only observed for individuals with less than 10 years of schooling–nearly everyone age 16 in 1997. To maintain the representativeness of the sample, all individuals age 16 in 1997 are dropped from regressions including PIAT scores, making the sample representative of males ages 12-15 in 1997. The large decline in sample size associated with specification (iv) is primarily due to the inclusion of PIAT scores and family income, both of which are missing for a sizeable fraction of the sample.

evade' arrest hypothesis, a 10% higher math PIAT score is associated with a 1.2% higher perceived chance of arrest.

The considerable variation in beliefs is not well explained by these rich measures of family background, geographic location, local arrest rates, age, race, and ability – the R^2 statistics for these regressions are no greater than 0.03. Yet, perceptions are fairly stable over time as seen in Figure 2, which shows the distribution of changes in the perceived probability of arrest from one year to the next (using kernel density estimation with a biweight kernel and bandwidth of 5). More than 25% of respondents do not change their beliefs about the probability of arrest between any two years. The correlation in perceptions between years is roughly 0.32.

Crime and Beliefs in the NYS

The NYS contains a random sample of 1,725 individuals (918 males) ages 11-17 in 1976. Respondents 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).[22] Data regarding family background and some neighborhood characteristics are available.

Table 4 reports the extent of selected criminal activities and arrest records from 1984 to 1986. Since most individuals are in their early twenties during these years, criminal participation is much lower than for the younger sample in the NLSY97. Yet, 18% still report stealing something worth less than $5 over this three-year period, and 9% report physically attacking someone. Substantially fewer individuals engage in more serious forms of theft. Nearly 12% report an arrest over the three-year span, although many of those arrests are for minor crimes. Only 1.9 percent are arrested for a property or violent crime.[23]

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 the number of arrests for violent crime

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

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

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 adjusted for non-reporting to the police, especially for violent crimes. (For example, 1986 arrest rates for larceny-theft were 5.5%, burglary, 7.4%, and assault, 20.4%.) However, both the number of crimes and number of arrests in this sample are quite small. Furthermore, the denominators are likely to be inflated due to duplication in reporting of crimes (e.g. some break-ins may also be reported as thefts by respondents).

Individuals were asked to report the probability (in increments of 0.1) that they would be arrested if they were to commit various crimes.[24] The distribution of reported probabilities of arrest in the NYS is shown in Figure 3. Table 5 reports average perceived probabilities of arrest in the NYS for four crimes: stealing something worth $5 or less, stealing something worth more than $50, breaking into a building or vehicle, and attacking someone to hurt or kill them. As with teenage boys in the NLSY97, perceived arrest rates are higher than official arrest rates in the U.S. But, the ranking of crimes by perceived arrest probability from most to least likely corresponds to the ranking of actual arrest rates across crime types. Interestingly, black and hispanic men in the NYS report higher perceived arrest probabilities for property crimes than do white men, in sharp contrast to the NLSY97 findings. However, the differences by race are small for all but petty theft.[25]

Table 6 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. Weighting beliefs by the number of crimes lowers perceived probabilities even more for all crimes except petty theft. Regardless of the sample, perceived probabilities of arrest are high compared to average arrest rates in the U.S.

The effects of age, race, family background, neighborhood conditions, and urban status on perceptions among young men are estimated using OLS and reported in Table 7. (Ordered probits produce similar conclusions.) Even after controlling for other background characteristics, blacks hold a signifi-

[24]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?"

[25]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 the types of crimes studied, or differences in respondents' age (early to mid-teens vs. mid-twenties). Racial differences in beliefs do not appear to differ dramatically by age, suggesting that the latter reason may not be too important.

cantly higher perceived probability of arrest than whites for petty theft, but not for other crimes. Men who grew up in intact families and have more educated mothers or fathers think that their likelihood of arrest is lower on average, although the differences are quite small and generally statistically insignificant. Consistent with official arrest patterns, men in rural areas hold higher perceived probabilities of arrest than those in urban communities.[26]

The 'broken windows' theory of Kelling and Wilson (1982) assumes that local neighborhood conditions affect individual perceptions about the likelihood of arrest and/or punishment and that those perceptions, in part, determine criminal behavior. The small and insignificant coefficients on neighborhood crime and disarray fail to support this theory. Instead, the estimates suggest that young men living in neighborhoods in which crime and 'broken windows' are a problem do not view their chances of arrest any differently from those living in cleaner and more orderly environments. We re-examine this issue below.

The substantial heterogeneity in beliefs is not well explained by rich background and neighborhood characteristics. As in the NLSY97, perceptions are largely idiosyncratic and difficult to explain; yet, they are also stable. Figure 4 shows the distribution of changes in beliefs from 1983 to 1986 for the sample. For each crime, about 20% of the young men do not change their perceived probability of arrest. About 60% change their perceived probability by twenty percent or less over three years. Only 10% of the young men revise their probabilities up or down by more than fifty percent for any given crime. Correlations between 1983 and 1986 perceptions are typically around one-third. We now turn to the issue of belief updating.

4 Information-Based Belief Updating

This section empirically studies factors that may cause individuals to change their beliefs about the probability of arrest. In the NLSY and NYS, we observe a single reported measure of the perceived probability of arrest, $p_{i,t}$, which we assume relates to $E(\pi|H_i^{t-1})$ from Section 2. The simple Bayesian structure above (see equation 3) suggests estimating the relationship between changes in perceptions and changes in environmental factors $Z_{i,t}$ (e.g. local arrest rates, metropolitan status, neighborhood characteristics, etc.), new arrests $A_{i,t-1}$ and crimes committed $c_{i,t-1}$ (both taking place between period $t-1$ and t) by the respondent as well as his siblings, $\tilde{A}_{i,t-1}$ and $\tilde{c}_{i,t-1}$:

$$\Delta p_{i,t} = \Delta Z_{i,t}\gamma + \phi A_{i,t-1} + \lambda c_{i,t-1} + \phi_s \tilde{A}_{i,t-1} + \lambda_s \tilde{c}_{i,t-1} + \xi_{i,t}. \tag{4}$$

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

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

$$p_{i,t} = X_i\beta + Z_{i,t}\gamma + \theta p_{i,t-1} + \phi A_{i,t-1} + \lambda c_{i,t-1} + \phi_s \tilde{A}_{i,t-1} + \lambda_s \tilde{c}_{i,t-1} + \varepsilon_{i,t}, \tag{5}$$

which allows for permanent individual-specific characteristics X_i (e.g. ability, race, family background etc.) and relaxes the implicit assumption of the Bayesian model that $\theta = 1$. With $|\theta| < 1$ and $Z_{i,t} = Z_i^*$ constant, beliefs would eventually converge to a steady state

$$p_i^*(X_i, Z_i^*) = X_i \frac{\beta}{1-\theta} + Z_i^* \frac{\gamma}{1-\theta}$$

if the individual and his siblings stopped committing crime and were never arrested again (ignoring changes in $\varepsilon_{i,t}$). Here, an individual's X_i characteristics determine his steady state level of beliefs. Changes in $Z_{i,t}$ characteristics will change steady state beliefs, perhaps through information gathered from others or from observing changes in local conditions. For example, moving to a new city or neighborhood may cause an individual to gradually shift his beliefs toward thinking the probability of arrest is higher or lower than previously thought, even if he does not engage in crime or face an arrest.

Equation (5) can be re-written as

$$p_{i,t} = (1-\theta)p_i^*(X_i, Z_{i,t-1}) + \theta p_{i,t-1} + \Delta Z_{i,t}\gamma + \phi A_{i,t-1} + \lambda c_{i,t-1} + \phi_s \tilde{A}_{i,t-1} + \lambda_s \tilde{c}_{i,t-1} + \varepsilon_{i,t},$$

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

With at least three periods of data, we can allow for unobserved individual fixed effects: $\varepsilon_{i,t} = \mu_i + \nu_{i,t}$ assuming that

$$E(\nu_{i,t}|p_i^{t-1}, Z_i^t, A_i^{t-1}, c_i^{t-1}, \tilde{A}_i^{t-1}, \tilde{c}_i^{t-1}) = 0 \qquad \forall t = 2, ..., T, \tag{6}$$

where $x_i^t = (x_{i1}, x_{i2}, ..., x_{it})$ for $x = p, Z, A, c, \tilde{A}, \tilde{c}$. Arellano and Honore (2001) refer to p, Z, A, c, $\tilde{A}$, and $\tilde{c}$ as 'pre-determined' variables. As they show, the assumption of equation (6) is fairly weak in that it does not rule out feedback effects of lagged dependent variables or disturbances on current and future values of the explanatory variables. In our context, current criminal and arrest decisions may be functions of earlier beliefs – an issue we will examine more closely in the following section. This general model with fixed effects can be estimated using GMM and the following moments:

$$\begin{aligned} E[p_{i,s}(\Delta p_{i,t} - \theta \Delta p_{i,t-1} - \Delta Y_{i,t}\Omega)] &= 0 \qquad \forall s \leq t-2 \\ E[Y_{i,s}(\Delta p_{i,t} - \theta \Delta p_{i,t-1} - \Delta Y_{i,t}\Omega)] &= 0 \qquad \forall s \leq t, \end{aligned}$$

where $Y_{i,t} = (Z_{i,t}, A_{i,t-1}, c_{i,t-1}, \tilde{A}_{i,t-1}, \tilde{c}_{i,t-1})$ and $\Omega = (\gamma, \phi, \lambda, \phi_s, \lambda_s)$.[27]

Table 8 reports estimates related to belief updating in the NLSY97 for the following: (A) OLS regression for the difference equation (4); (B) OLS regression for the quasi-difference equation (5); and (C) GMM for the quasi-difference equation (5) accounting for individual fixed effects. Each panel reports two specifications. The first includes indicators for whether the individual or his male siblings committed crime or were arrested (for a violent or property crime) between survey dates. The second includes indicators for the actual number of times individuals and their siblings committed crimes and were arrested.[28] Measures based on sibling crimes and arrests refer to male siblings who are also in the main NLSY97 sample. As a result, their ages are always within a few years of the respondent.[29] In general, all specifications show evidence of belief updating in response to the respondent's own criminal history. Individuals who reported stealing something worth more than \$50 or selling drugs were likely to report a lower perceived probability of arrest (conditional on prior beliefs and the arrest outcome) in the next survey year. While the effects of at least one crime on perceptions are statistically significant in all specifications, the effects of an arrest for a violent or property crime generally are not. While the specifications that do not include individual fixed effects (panels A and B) produce positive point estimates for arrests (as expected), those of panel C are negative and insignificant. There appear to be too few arrests in the data to precisely estimate the effect of arrests on beliefs in the NLSY97. As shown at the bottom of Table 8, a joint F-test of whether the coefficients on all individual crime and arrest variables are zero is strongly rejected in most specifications.

The effects of sibling crime and arrests are less precisely estimated given that only 27% of the respondents have at least one sibling that is also in the NLSY97 sample. Still, a number of coefficient estimates on measures of sibling crime are statistically significant and negative, as expected. Joint

[27] See Arellano and Honore (2001) for a comprehensive discussion of estimation with panel data and fixed effects.

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

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

F-tests for whether the sibling crime and arrest coefficients are zero is rejected in half of the specifications. Alternatively, a joint F-test for whether the coefficients on sibling crimes and arrests equal the corresponding coefficients on respondent crime and arrests cannot be rejected for any specification.

The most noticeable difference between the OLS and GMM estimates of equation (5) is the change in the estimated coefficient on the previous measure of beliefs. After controlling for fixed effects, the autocorrelation in the perceived probability of arrest (θ) drops from 0.3 to below 0.06. Heterogeneity in unobserved fixed effects, μ_i, across individuals implies idiosyncratic variation in steady state levels of beliefs. The fact that θ is estimated to be quite small when fixed effects are included suggests that any deviation from an individual's steady state level of beliefs in response to new information (e.g. an arrest or non-arrest) fades out very quickly. So, an arrest may reduce the perceived probability for a year or so, but it has little lasting effect on beliefs.

A more limited analysis is performed using young men in the NYS. Because the NYS only records beliefs for two periods, we cannot estimate the quasi-difference model with fixed effects using the GMM procedure outlined earlier. In Table 9, we report estimates of equation (5) using 1983 and 1986 measures of beliefs, accounting for crimes and arrests that take place between the two surveys (estimates of the first-difference specification are quite similar).[30] Again, we employ two specifications for each type of crime studied. The first includes an indicator variable for whether the individual committed the crime under study (e.g. in column 1, the indicator is one if the individual reported stealing something worth less than \$5 and zero otherwise) or was arrested for a violent or property crime during the 1984-86 period. The second includes measures of the number of crimes committed and arrests over that period.

As in the NLSY97, these men report lower perceived probabilities of arrest for all crime categories at the end of 1986 if they engaged in that type of crime in 1984-86 (three of the four estimates are statistically significant). Coefficients on arrest are always positive, but they are only significantly different from zero for break-ins. Joint tests of whether the coefficients on crime and arrests are zero are rejected in nearly all of the columns. While the model above suggests that the net effect of a crime and arrest should be negative, the specifications with only an indicator for committing a crime and getting arrested generally reveal a coefficient on the indicator for crime that is larger in absolute value than the coefficient on the arrest indicator. This is because those who are arrested commit more than one crime, on average. Looking at the specifications controlling for the number of crimes and arrests, we always observe a larger coefficient on an arrest than on a crime. Thus, the net effect of a crime

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

and arrest on the perceived probability of arrest is always positive.

It is interesting to note that using measures for any arrest rather than arrests for more serious property and violent crimes (as in Table 9) generally produces smaller and insignificant effects on beliefs (except for small thefts). This suggests that police attempts to crack down on vagrancy, public intoxication, and other petty crimes are not likely to influence beliefs about the probability of arrest for more serious crimes in any significant way.

Table 9 also reports coefficient estimates on central city status and rural residential status. The effects of these measures are insignificant once we control for crime and arrest histories and previous measures of beliefs (in contrast to those in Table 7). Measures of neighborhood lawlessness and disarray also have no significant effect on beliefs. Again, we find no evidence to support the 'broken windows' theory of Wilson and Kelling (1982).

While we have do not have sibling measures of beliefs or crime in the NYS, one might wonder whether information about the arrests of other random criminals has any affect on beliefs as Sah's (1991) theory would suggest. To that end, we examine whether individuals who are victimized by a crime alter their beliefs in response. The underlying assumption here is that victims 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 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 official arrest rates reported earlier. Then, we should expect, on average, that individuals will adjust the probability of arrest downward after a victimization.[31] The estimated coefficients on victimization are small and statistically insignificant for all crimes in Table 9. While not an ideal test of information from the arrest outcomes of others, these estimates suggest that individuals put little weight on the information provided by the crime and arrest outcomes of random criminals. Arrest probabilities may be too individual-specific to make such information 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

[31]Of course, if those who observe an arrest adjust their beliefs upward much more than those who do not observe an arrest adjust their beliefs down, this need not be the case. Given that official arrest rates range from 5-20% for the crimes under study, those observing an arrest would have to adjust their beliefs upwards by 5 to 20 times as much as those not observing an arrest adjust theirs downward for the effects to cancel. This is unlikely, given that the estimated negative coefficients on (own and sibling) crime measures remain significantly negative when leaving out arrest outcomes in updating regressions (i.e. Tables 8 and 9).

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. Only an information-based model of belief updating can readily explain both findings. The fact that sibling criminal and arrest histories affect beliefs in a similar way only strengthens this conclusion. The importance of an individual's own criminal and arrest history in determining beliefs strongly supports the very simple model outlined in Section 2 and developed further in Lochner (2002). Sah's (1991) theory also finds some support in that the criminal and arrest history of an individual's siblings affects beliefs about the probability of arrest, but information about arrest outcomes from other random persons does not seem to be important. Taken together, these results suggest a limited role for learning from others.

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. And, do they behave differently in periods when they report a high perceived probability of arrest than when they report a low probability? Rational choice theory suggests that (holding all else constant), individuals facing a higher probability of arrest and/or punishment should commit less crime. We examine this relationship in the NLSY97 and NYS.

Assuming the benefit-cost ratio of crime in Section 2 is given by $R_{i,t} = AW_{i,t} - \omega_{i,t}$ produces the following latent index decision model for crime:

$$c_{i,t} = \begin{cases} 1 & \text{if } c^*_{i,t} \equiv AW_{i,t} - Bp_{i,t} - \omega_{i,t} > 0 \\ 0 & \text{otherwise} \end{cases}$$

If $\omega_{i,t}$ is iid logistic over time and across individuals, this implies a standard logit model for criminal participation. Since perceptions cannot have been affected by subsequent criminal behavior (and their arrest outcomes), we explore the effects of elicited perceptions on crime reported in the following survey. This leaves us with three years of belief-crime data in the NLSY97 and a single cross-section in the NYS.

Using maximum likelihood, we estimate this logit model for self-reported criminal participation in both data sets. In the NLSY97, we control for age, race, ethnicity, whether or not the youth lived with both his natural parents, whether or not the youth's mother was a teenager at birth, and math PIAT scores in addition to the perceived probability of arrest for auto theft. The estimated coefficients on the perceived probability are negative in specifications for auto theft and for thefts of something worth more than $50, suggesting that an increase of 0.1 in the perceived probability of arrest reduces the probability of stealing a car by almost 5% and the probability of stealing something worth more than $50 by a little more than 3%.[32] As a simple check on these results, we also estimate two other logit specifications for whether or not someone smoked a cigarette or drank alcohol in the last 30 days. In percentage terms, the effects of the perceived probability of arrest for auto theft are much smaller (1% for smoking and 0.5% for drinking). This is re-assuring, since we would not expect the probability of arrest for auto theft to be very highly correlated with the probability that these young males will be punished for smoking or drinking. Additionally, we note that specifications which also include the county-level arrest rate produce similar findings. Official arrest rates have no significant impact on participation in crime for the NLSY97 sample.

A similar approach can be taken with the NYS, examining the effects of beliefs in 1983 on crime committed over the 1984-86 period. Here, we have crime-specific beliefs, which we include in the logits along with controls for age, race/ethnicity, whether the respondent lived with both natural parents in 1976, whether parental income was below $10,000 in 1976, and rural and central city residential status. All estimated coefficients on the crime-specific perceived probability of arrest are negative, supporting the case for deterrence.[33]

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 the influence of unobserved tastes for crime that are correlated with arrest probability perceptions. Two sets of results suggest that this may not be an important problem. First, the NLSY97 findings suggest that the effects of beliefs about the probability of arrest for auto theft are quite small (in percentage terms) for minor delinquent activities like smoking and drinking – much smaller than the effects on theft. Second, the estimated effects of beliefs on crime in the NYS remain even after controlling for parental and peer approval levels for crime as well as the individual's own moral attitudes towards crime.[34]

[32] The coefficient on the perceived probability of arrest in the auto theft logit is -0.485 with a standard error of 0.256, and the corresponding coefficient in the logit for thefts of more than $50 is -0.346 with a standard error of 0.131. Specifications which also include the perceived conditional probability of going to jail if arrested yield similar estimates for the impact of arrest probabilities. Specifications which control for the perceived unconditional probability of going to jail (i.e. the interaction of the probability of arrest with the probability of going to jail conditional on arrest) produce qualitatively similar results.

[33] The estimated coefficient for thefts of less than $5 is -1.5 (standard error of 0.5), thefts greater than $50, -0.7 (0.7), break-ins, -1.1 (0.9), and attacks, -1.1 (0.4).

[34] Specifically, these specifications control for whether the respondent's parents or peers would disapprove of them stealing something and whether they themselves believe stealing is wrong.

If one is willing to treat these estimates as the deterrent effect of perceived arrest probabilities, it is possible to study the extent to which differences in beliefs are responsible for differences in criminal participation by race or ability. The estimated 8 percentage point difference in perceived arrest probabilities between whites and blacks (Table 3, column iv) implies a 3.8% higher participation rate in auto theft by blacks. Hispanics are predicted to have a 4.2% 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 2.9%. These simple comparisons suggest that important variation in criminal participation rates across individuals may be due to differences in information and beliefs.

Thus far, we have only examined the cross-sectional relationship between beliefs and criminal behavior. Given the potential for correlation between unobserved tastes for crime and beliefs about the probability of arrest, one would like to control for unobserved fixed effects in the criminal choice equation. However, it is generally difficult to estimate dynamic discrete choice models with fixed effects when all regressors are not strictly exogenous (in our context, perceptions are predetermined but not strictly exogenous).[35] Furthermore, once fixed effects are introduced, it is no longer possible to estimate the average effect of changes in the perceived probability of arrest on the probability of committing crime.

We take a different approach motivated by the model outlined in Section 2. In particular, we use the NLSY97 to examine the effects of an arrest for theft, which is assumed to be random conditional on the number of thefts of something worth more than \$50, on beliefs and subsequent crime. The model suggests that the perceived probability should increase while crime should decline among those arrested. Matching individuals on the number of thefts, we estimate the average effect of an arrest on the perceived probability of arrest for auto theft and on thefts of greater than \$50 (where the average is taken over the distribution of crimes committed by those who are arrested).[36] Consistent

[35] A regressor is strictly exogenous if it is independent of all past, present, and future disturbances, although it may be correlated with individual fixed effects. Predetermined regressors may be correlated with past disturbances but must be uncorrelated with present and future disturbances. The conditional logit approach of Chamberlain (1980) and the conditional maximum score approach of Manski (1987) require strict exogeneity of all regressors. Honore and Kyriazidou (2000) allow for lagged dependent variables, but all other regressors must be strictly exogenous. More recently, Honore and Lewbel (2002) do not require strictly exogenous regressors, but they require a 'special' regressor with conditions that are not well-suited to the problem at hand.

[36] For an outcome y_{it} (either crimes committed in period t or the change in perceptions from period $t-1$ to t), we first estimate the average outcome for each level of crime and arrests: $\bar{y}_t(c,A) = \frac{1}{N(c,A)} \sum_{i:(c_{i,t-1},A_{i,t-1})=(c,A)} y_{i,t}$ for all $c \in \{1,2,3,...,\bar{c}\}$ and $A \in \{0,1\}$, where $N(c,A)$ is the number of persons who committed c crimes and were arrested A times in period $t-1$. Then, compute $\bar{\Delta}(c) = \bar{y}_t(c,1) - \bar{y}_t(c,0)$, the average difference in outcomes for those who are arrested and those who are not given their crime level c. Finally, we compute the average effect (over the crime distribution of arrestees), $\bar{\Delta} = \sum_{c=1}^{\bar{c}} f(c)\bar{\Delta}(c)$, where $f(c)$ is the fraction of all arrestees who committed c crimes in period $t-1$.

with Table 8, we find that the average perceived probability of arrest increases 6.2 (standard error of 6.7) percentage points more for those who are arrested than those who are not. We find mixed results on crime. The probability that someone steals something worth more than $50 increases by 0.05 (standard error of 0.05), but the average number of thefts worth more than $50 decreases by 0.92 (standard error of 0.52). The latter estimate suggests that the number of crimes committed declines in response to an increase in arrests as predicted by deterrence theory. However, it is impossible to say whether the effect on crime comes through changes in beliefs about the probability of arrest or whether an arrest causes individuals to commit less crime in subsequent years because they fear an increase in potential punishments if they are caught again.[37]

6 Conclusions

Empirically, we uncover substantial heterogeneity in beliefs 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, and those beliefs are fairly stable across time for individuals. Perceived arrest rates are lower, on average, among those actively engaged in crime, which is consistent with standard deterrence theory as well as an information-based model of belief updating. 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 beliefs can be explained by differences in family background, neighborhood, or cognitive abilities.

Beliefs are correlated with county-level official arrest rates and metropolitan or urban residential status. But, contrary to the 'broken windows' theory developed by Wilson and Kelling (1982), perceptions are not correlated with other neighborhood conditions like 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, individual beliefs about their own probability of arrest are largely idiosyncratic, stable, and unrelated to the local environment. It is difficult to know whether variation in beliefs across individuals reflects actual variation in the true probability of arrest or simple differences in beliefs. 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. Beliefs respond similarly to changes in the criminal and arrest ac-

[37] As such, arrests may not be a valid instrument for beliefs in the criminal choice equation.

tivity of their siblings, suggesting that individuals do share information of this sort among similarly aged family members.

Finally, we find evidence consistent with deterrence theory. Cross-sectional variation in criminal participation is negatively correlated with beliefs about the probability of arrest, and individuals respond to an arrest by increasing their perceived probability of arrest and scaling back their criminal activity. Given the difficulty in analyzing this issue in the presence of unobserved tastes for crime or risk, more research on this question certainly seems warranted.

Overall, the empirical findings support the economic model of crime and belief updating outlined in Section 2 of this paper. Beliefs are heterogeneous and idiosyncratic. They also respond to individual and sibling arrests and non-arrests in predictable ways. While most of the literature on criminal deterrence assumes that individuals know true arrest rates and that an increase in those arrest rates will immediately deter crime, this paper suggests that this may not be the case. Individuals appear to learn about the probability of arrest as they gain more experience with the criminal justice system. As a result, responses to changes in enforcement are likely to differ across individuals with different crime and arrest histories, and the full impacts of any enforcement policy may not be realized for many years.

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Figure 1: Distribution of Perceived Probability of Arrest for Auto Theft (NLSY97)

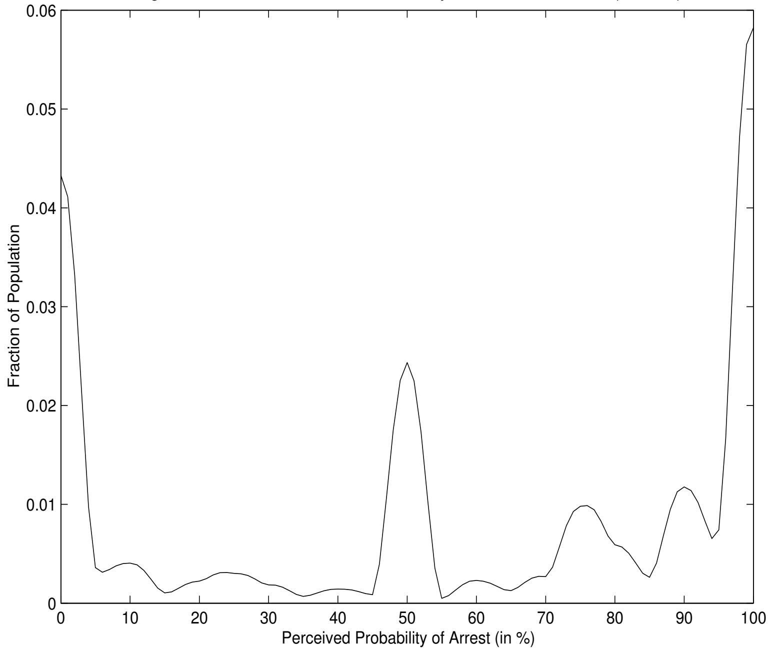

Figure 2: Distribution of Changes in Perceived Probability of Arrest for Auto Theft (NLSY97)

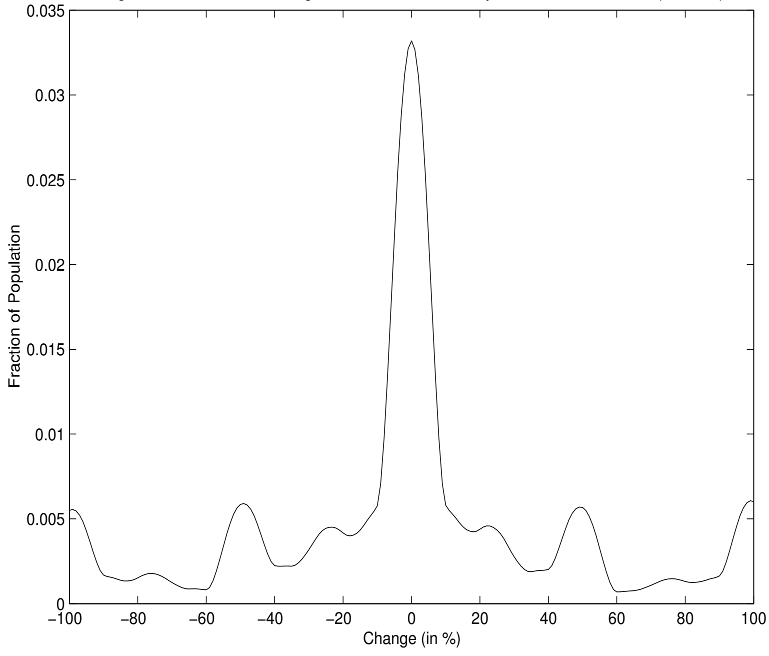

Figure 3: Distribution of Perceived Probability of Arrest in NYS

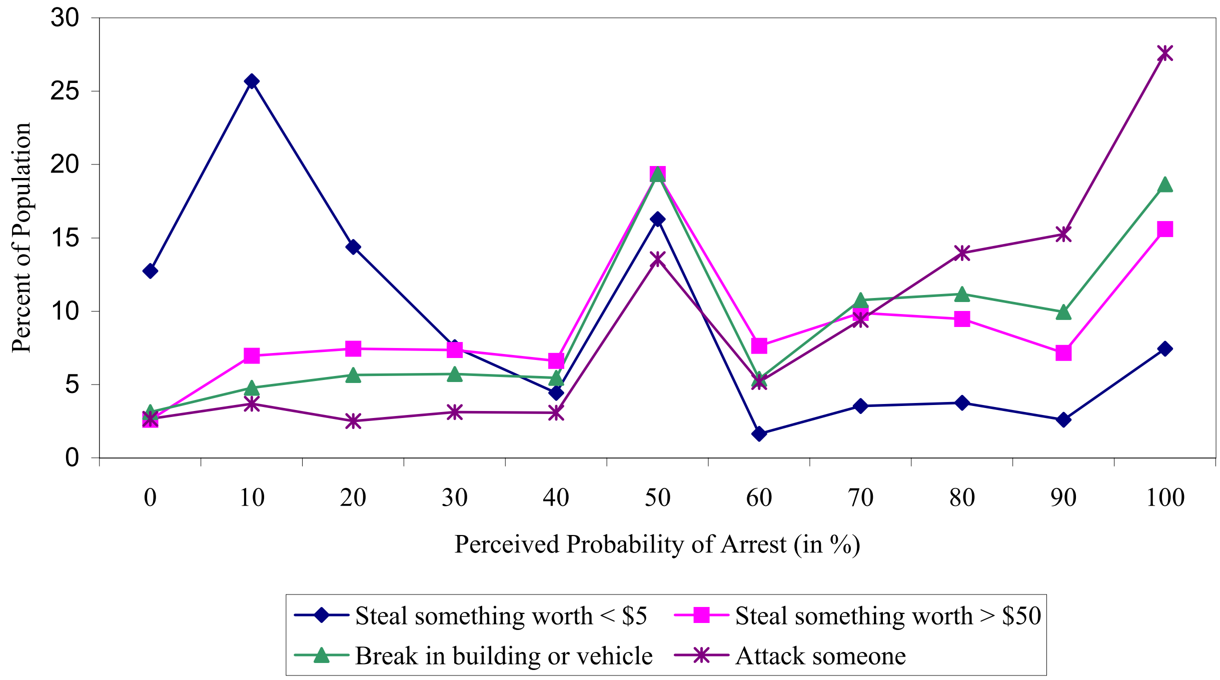

Figure 4: Distribution of Changes in Perceived Probability of Arrest in NYS

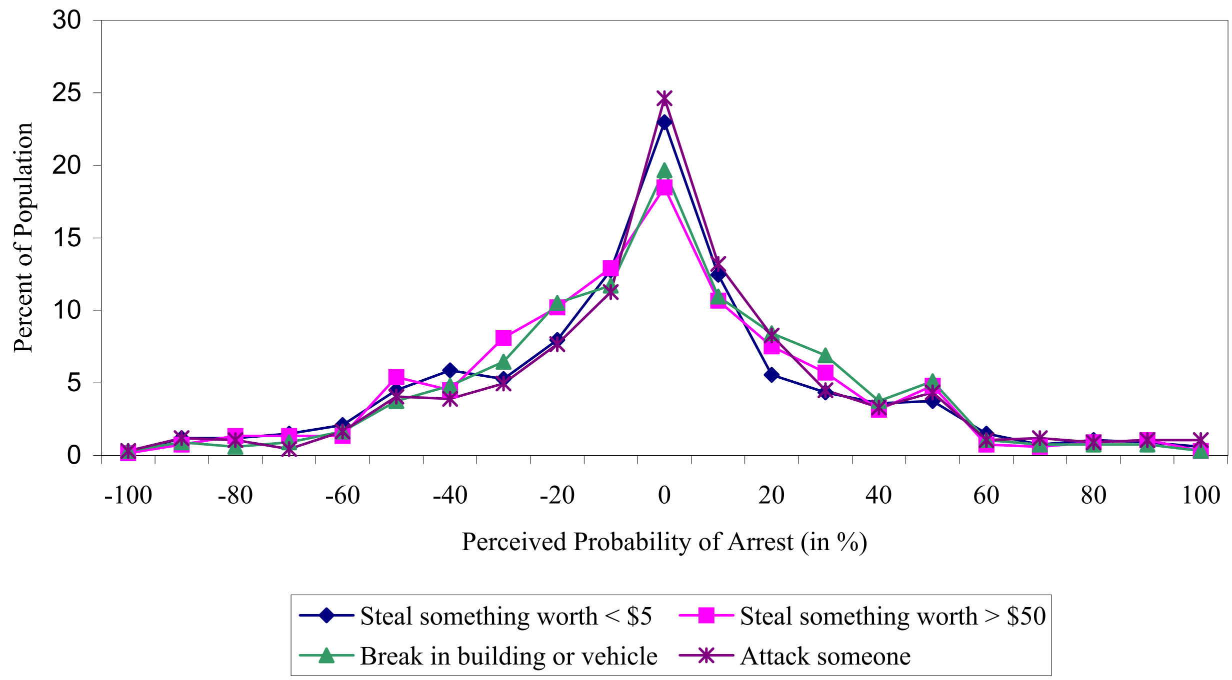

Table 1: Annual Self-Reported Crime and Arrests Among Males in the NLSY97

	All	Blacks	Hispanics	Whites
Number of respondents	4,559	1,169	977	2,413
Percent who stole something worth > $50	5.45	6.37	6.31	5.09
Percent who stole a vehicle	1.20	1.31	1.77	1.06
Avg. number of thefts > $50	0.36	0.44	0.57	0.30
Avg. number of thefts > $50 (of those who stole)	6.69	7.18	9.16	5.99
Percent arrested for any offense	8.40	11.28	9.13	7.63
Percent arrested for theft	1.63	2.11	1.58	1.54
Avg. number of arrests for theft	0.02	0.03	0.02	0.02
Persons arrested for theft / persons who stole > $50	0.30	0.33	0.25	0.30
Persons arrested for theft / persons who stole a vehicle	1.36	1.61	0.89	1.45
Arrests for theft / number of thefts > $50	0.05	0.06	0.04	0.06

Notes:

All measures computed using panel sample weights.

Table 2: Average Perceived Probabilities (in %) of Arrest for Auto Theft (Males in NLSY97)

	All	Blacks	Hispanics	Whites
A) All Individuals	60.53	51.79	53.67	63.74
	(0.48)	(1.00)	(1.04)	(0.59)
B) Individuals who reported stealing	50.46	43.49	43.61	53.88
something worth more than $50	(1.67)	(3.57)	(2.81)	(2.22)
C) Individuals who reported stealing a car	44.78	40.50	39.72	47.42
	(2.97)	(5.82)	(4.65)	(4.16)
D) Weighted by number of thefts worth	39.31	35.76	35.77	41.71
more than $50	(3.02)	(6.50)	(5.96)	(4.09)

Notes:

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

Table 3: OLS Estimates of Perceived Probability (in %) of Arrest for Auto Theft (Males in NLSY97)

Variable	(i)	(ii)	(iii)	(iv)
county arrest rate for motor vehicle theft	0.130	0.076	0.034	0.054
	(0.038)	(0.038)	(0.039)	(0.049)
age		-0.602	-0.634	-0.293
		(0.338)	(0.337)	(0.566)
black		-11.671	-11.625	-7.821
		(1.200)	(1.200)	(1.829)
hispanic		-9.600	-9.100	-8.713
		(1.239)	(1.250)	(1.799)
living in MSA			-4.699	-3.635
			(1.266)	(1.625)
family income less than $10,000				2.430
				(2.267)
living with both natural parents in1997				0.278
				(1.373)
PIAT score (percentile)				0.120
				(0.021)
mother a teenager at birth				-1.620
				(2.137)
R-square	0.002	0.019	0.020	0.030
Number of observations	13,800	13,800	13,800	7,141

Notes:

All specifications are weighted by panel weights and include a constant. Specifications (ii)-(iv) also control for year dummies. Standard errors, corrected for clustering across years for each individual, are in parentheses.

Table 4: Total Self-Reported Crimes and Arrests from 1984-1986 (Males in NYS)

Percent black	16.40
Percent hispanic	4.25
Percent who stole something worth < $5	17.70
Avg. number of thefts < $5	2.21
Percent who stole something worth > $50	3.72
Avg. number of thefts > $50	0.23
Percent who broke into a building or vehicle	2.29
Avg. number of breakins	0.12
Percent attacking someone to hurt or kill them	8.88
Avg. number of attacks	0.25
Percent arrested	11.90
Percent arrested for a property or violent offense	1.86
Average number of arrests	0.17
Average number of arrests for property or violent offense	0.02

Notes:

Arrests for property offenses include various forms of theft, evading payment, burglary, breaking and entering, and dealing in stolen goods. Arrests for violent offenses include assault, robbery, and harassment.

Table 5: Average Perceived Probabilities (in %) of Arrest (Males in NYS, 1983 & 1986)

Crime	All	Blacks	Hispanics	Whites
(i) Steal something worth $5 or less	33.84	43.55	38.37	31.86
	(0.90)	(2.54)	(4.60)	(0.97)
(ii) Steal something worth more than $50	57.81	63.10	58.57	56.78
	(0.87)	(2.25)	(4.49)	(0.97)
(iii) Break into a building or vehicle	62.49	67.22	66.33	61.54
	(0.88)	(2.26)	(4.71)	(0.98)
(iv) Attack someone to hurt or kill them	72.00	72.12	70.61	72.08
	(0.82)	(2.18)	(5.58)	(0.90)

Notes:
Standard errors, corrected for clustering across years for each individual, are in parentheses.

Table 6: Mean Perceived Probabilities (in %) of Arrest (Males in 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	20.43
(standard error)	(0.97)	(1.72)	(4.97)
[sample size]	[1,307]	[161]	[161]
(ii) Steal something worth more than $50	57.94	53.00	46.55
(standard error)	(0.88)	(0.88)	(0.88)
[sample size]	[1,428]	[40]	[40]
(iii) Break into a building or vehicle	62.77	51.67	44.67
(standard error)	(0.89)	(6.12)	(16.12)
[sample size]	[1,432]	[36]	[36]
(iv) Attack someone to hurt or kill them	73.43	54.78	52.76
(standard error)	(0.81)	(3.34)	(4.05)
[sample size]	[1,355]	[113]	[113]

Notes:

Standard errors, corrected for clustering across years for each individual, are in parentheses. Sample sizes in brackets.

Table 7: OLS Estimates of Perceived Probability (in %) of Arrest Among Males in NYS

Variable	(i) Steal something worth < $5	(ii) Steal something worth > $50	(iii) Break into building or vehicle	(iv) Attack Someone
Age	-0.596	-1.111	-0.430	0.393
	(0.343)	(0.340)	(0.344)	(0.350)
Black	9.866	4.974	4.958	-0.721
	(3.559)	(3.257)	(3.260)	(3.189)
Hispanic	5.054	1.344	4.964	-0.042
	(5.596)	(5.362)	(5.267)	(5.668)
Rural	4.625	6.866	5.129	3.121
	(2.163)	(2.083)	(2.208)	(2.129)
Central city	-1.813	-1.108	0.584	0.952
	(2.161)	(2.108)	(2.097)	(1.937)
Living with both parents in 1976	-1.545	-0.807	-5.109	-1.053
	(2.387)	(2.353)	(2.333)	(2.216)
Family income < $10,000 in1976	2.982	0.383	-1.278	-2.039
	(2.606)	(2.490)	(2.592)	(2.442)
Mother graduate from HS	-4.323	-1.189	-2.032	-0.819
	(2.354)	(2.237)	(2.225)	(2.057)
Father graduate from HS	-1.338	-2.554	-3.822	-0.862
	(2.364)	(2.258)	(2.426)	(2.247)
Neighborhood crime a problem	-1.477	0.845	0.354	-2.472
	(1.867)	(1.799)	(1.777)	(1.745)
Neighborhood disarray a problem	0.453	0.212	-1.737	1.444
	(2.223)	(2.162)	(2.181)	(2.107)
R-square	0.039	0.031	0.025	0.006

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

Table 8: Belief Updating Among Males in the NLSY97
Dependent Variable: Perceived probability of arrest (in %)

	(A) OLS (First differences)		(B) OLS (Quasi-first differences)		(C) GMM (Quasi-first diff. with fixed effects)	
Variable	(i)	(ii)	(i)	(ii)	(i)	(ii)
County arrest rate (in percentage terms)	-0.032	-0.030	0.043	0.041	0.015	-0.006
	(0.047)	(0.047)	(0.039)	(0.039)	(0.096)	(0.096)
Perceived probability of arrest in previous year			0.300	0.300	0.055	0.058
(in percentage terms)			(0.012)	(0.012)	(0.034)	(0.034)
Stole something worth > $50	-2.916		-6.989		-3.850	
in previous year	(2.306)		(2.168)		(3.401)	
Sold drugs in previous year	-4.049		-5.984		-5.007	
	(1.708)		(1.690)		(2.587)	
Arrested for theft in previous year	7.603		7.618		-2.289	
	(4.039)		(3.797)		(6.034)	
Num. times stole something worth > $50		-0.286		-0.313		-0.463
in previous year		(0.126)		(0.114)		(0.204)
Num. times sold drugs in previous year		0.013		-0.111		0.005
		(0.042)		(0.041)		(0.068)
Num. times arrested for theft in previous year		4.345		3.501		-6.152
		(3.126)		(2.955)		(5.284)
Sibling stole something worth > $50	3.510		1.042		-7.925	
in previous year	(3.982)		(3.888)		(5.850)	
Sibling sold drugs in previous year	-6.352		-7.975		-0.898	
	(2.862)		(2.900)		(6.046)	
Sibling arrested for theft in previous year	-4.271		-2.202		11.618	
	(6.687)		(7.372)		(10.521)	
Num. times siblings stole something		-0.462		-0.395		-0.465
worth > $50 in previous year		(0.209)		(0.265)		(0.410)
Num. times siblings sold drugs		-0.064		-0.120		-0.054
in previous year		(0.064)		(0.066)		(0.113)
Num. times sibling was arrested for theft		1.100		2.287		1.807
in previous year		(4.211)		(4.463)		(7.157)
Tests (P-value):						
No effect of respondent information	0.012	0.113	0.000	0.000	0.115	0.076
No effect of sibling information	0.121	0.037	0.035	0.095	0.494	0.659
Equal respondent and sibling information	0.305	0.387	0.300	0.977	0.616	0.797

Notes:

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

Table 9: Belief Updating Among Males in the NYS
Dependent Variable: Perceived Probability of Arrest (in %) in 1986

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

Notes:

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