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MARKET WAGES AND YOUTH CRIME

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ABSTRACT

Youth crime is widespread. To study the effect of market wages on youth crime, I analyze a time-allocation model in which consumers face parametric wages and diminishing marginal returns to crime. Under these assumptions, an individual who works will commit crime if the returns to the first hour of crime exceed his market wage. This decision rule imposes considerable structure on the econometric model, which I estimate using data from the National Longitudinal Survey Youth Cohort. The empirical model provides estimates of the determinants of criminal returns and of the wage responsiveness of criminal participation. Young men's behavior appears to be very responsive to price incentives. My estimates suggest that falling real wages may have been an important determinant of rising youth crime over the past two decades. Moreover, wages explain an important component of the racial differential in criminal participation, and they largely explain the age distribution of crime.

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I. INTRODUCTION

Crime is widespread among young men. Thirty-five percent of all Philadelphia males born in 1945 were arrested before the age of eighteen, and one-third of all California men born in 1956 were arrested between the ages of 18 and 30 (Wolfgang, Figlio, and Sellin 1972; Tillman 1987).[1] The 1990 Census counted 1.1 million persons in jail, the vast majority of whom were men in their twenties and thirties.

For economists, a natural question is whether such widespread youth crime is responsive to labor market incentives. In a time-allocation model, work is the alternative to crime. Therefore crime committed by optimizing consumers should respond to changes in wages.

Surprisingly, however, this question has received little attention. Although economists have studied crime now for some time, most research has focused on the effects of criminal justice sanctions.[2] There appears to be only one study that has tested whether market wages affect individuals' decisions about whether to commit crime (Schmidt and Witte 1984). Because that study was based on a sample of released prisoners, however, it is not clear whether its results--that wages have little effect on crime--extend to the more general population.

Understanding the role of wages may help explain a number of facts about crime. First, real wages have fallen over the past twenty years, especially for young men (Bound and Johnson 1992, Katz and Murphy 1992). Over the same period, youth arrest rates have risen substantially (Federal Bureau of Investigation, 1990b). It is of great interest to

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[1] For the most part, these arrests are for substantial crimes, not for traffic infractions or trivial offenses. Tillman's arrests, for example, pertain only to crimes sufficiently severe so as to warrant a possible jail term upon conviction.

[2] See, e.g., Becker (1968), Sjoquist (1973), Ehrlich (1973), Wolpin (1980), Witte (1980), Myers (1983), Tauchen, Witte, and Griesinger (1988), Grogger (1991). In addition, Freeman (1991), Bound and Freeman (1992), and Grogger (1995) recently have estimated the effect of arrests and jail sentences on youth employment and earnings.

determine how much of the increase in youth crime can be attributed to the decline in youth wages.

Second, police records typically show that blacks participate in crime at a much greater rate than whites. At the same time, we know that blacks generally earn less than whites, even after controlling for numerous observable characteristics. If crime is responsive to wages, then the black-white wage gap may explain part of the black-white difference in crime rates.

Third, the likelihood of committing crime typically increases with age until the late teens and then declines. This relationship is quite robust, and seems to hold up across countries, at different points in time, and irrespective of the way crime is measured. Although criminologists have studied this phenomenon extensively, they have yet to explain it (Gottfredson and Hirschi 1986). If criminal behavior responds to wages, then the age distribution of crime may well be a labor market phenomenon. Wages represent the opportunity cost of committing crime, and rise steeply with age during the early part of one's career.

The primary goals of this paper are to estimate the effect of market wages on youth crime and determine whether wages can explain the recent trend in crime and its distribution by race and age. I focus exclusively on property crimes, that is, crimes from which the perpetrator may acquire income. Although this rules out pure crimes of violence, it captures the vast majority of all reported crime. Among crimes tabulated by the FBI, only 8.2 percent are pure crimes of violence such as murder, rape, or aggravated assault (Federal Bureau of Investigation 1992).

I begin by analyzing a time-allocation model in which consumers decide how much crime to commit and how much to work on the market as a function of their returns to crime and their wages. The goal of this exercise is to motivate an econometric model of youth behavior that can be identified from the limited data at my disposal. My data include information on income from crime and a crime participation dummy constructed from this criminal income measure. I have no reliable information on the amount of time that criminals spend committing crime, nor on the number of crimes that they commit, nor on their earnings per crime. The conceptual model illustrates the types of assumptions one needs to estimate the model from this limited information. It also aids in specifying the econometric model and in interpreting its parameters.

I consider a consumer who is amoral in the sense that an hour spent committing crime causes no more disutility than an hour spent working. I also assume that the consumer faces a parametric market wage and diminishing marginal returns to crime. The resulting model is formally similar to Gronau's (1977) model of the allocation of time between leisure, market work, and work at home. In my model, however, crime takes the place of home production.

Provided the consumer works on the labor market, his criminal participation decision is particularly simple. A necessary condition for committing crime is that the returns to the first hour of crime exceed the market wage. This condition is the key to estimating the effect of wages on criminal participation.

I estimate the econometric model using data from the National Longitudinal Survey of Youth (NLSY). In 1980, the NLSY asked respondents about crimes they committed in the previous year. One measure from the NLSY crime module--a crime participation dummy constructed from responses to a question about criminal income--appears to have greater validity than other self-reported measures of crime.

The econometric model provides estimates of the determinants of criminal returns. It also provides estimates of the elasticity of criminal participation with respect to the market wage. With these estimates, I then ask whether labor market incentives can explain the observed variation in crime over time, by race, and by age.

II. THEORETICAL FRAMEWORK

The objective of this section is to motivate an econometric model of youth behavior. Therefore, let us first examine the data to see what sort of behavior the model needs to explain. Table 1 presents data from young men in the NLSY who were not in school or in the military in 1980.[3] This is a very crime-prone segment of the population, since the sample members are both young, with an age range of 17 to 23, and relatively uneducated. In the table I cross-tabulate employment status by participation in crime for the year 1979 based on the data from the 1980 interview. Youths who reported positive weeks worked in 1979 are counted as employed; those who reported any income from crime that year are counted as criminals.

There are two noteworthy features of the table. First, nearly one-fourth of the sample admitted to earning income from crime over the previous year. Second, almost everyone worked, whether they committed crime or not. For the purpose of guiding the modeling exercise, the latter is the more important observation. It indicates that the goal of the model should be to explain crime in a world in which almost everyone works on the labor market.

A model capable of capturing such behavior begins with a consumer who values only consumption and leisure, where leisure is defined as time spent neither working nor committing crime. He chooses time at market work h_m and time committing crime h_c to maximize utility U, which increases at a decreasing rate in both consumption c and leisure L. The consumer faces a parametric market wage w and concave returns to crime $r(h_c)$. The function $r(h_c)$ can be thought of as embodying both the technological relationship by which effort is transformed into stolen goods, and the means by which stolen goods are exchanged for income. Concavity thus reflects diminishing marginal productivity. The more crimes the consumer commits, the less remunerative is each additional crime.

Although much previous work on the economics of crime has focused on uncertainty in the returns to crime, I take no explicit account of it here. This is for a simple

[3] Other minor exclusion restrictions are imposed on the sample as well; these are discussed in detail in Section IV.

reason: the data do not contain measures of the uncertainty of criminal income or of consumers' attitudes toward risk. Though it would be desirable to incorporate uncertainty into the empirical model, such an extension will have to wait until richer data become available.

The consumer's problem can be written as

$$\max U(c, L)$$
$$\text{s.t.} \quad c = wh_m + r(h_c) + A$$
$$L = T - h_m - h_c$$

where T is the amount of time available and A is non-labor income. The amorality assumption is reflected in the symmetry with which h_m and h_c enter the consumer's utility function. In words, the consumer experiences no greater disutility from an hour of crime than from an hour of work.

The model is formally similar to Gronau's (1977) model of the consumer's allocation of time between leisure, market work, and home production, where in my model, crime takes the place of home production.[4] To analyze the model and lay the groundwork for the econometrics, I follow the approach of Heckman (1974) and Heckman and MaCurdy (1981), rewriting the consumer's marginal rate of substitution (MRS) as

$$MRS(c, L) = \frac{U_2(wh_m + A + r(h_c), T - h_c - h_m)}{U_1(wh_m + A + r(h_c), T - h_c - h_m)}$$
$$= m(h_m, A + r(h_c), T - h_c).$$

Writing the consumer's MRS in this way highlights an important feature of the model: the consumer's choice of criminal hours influences his choice of market hours by changing his

4 Lemieux, Fortin, and Frechette (1994) use a variant of Gronau's model to study the supply of labor into the untaxed sector, a type of illegal activity quite different from that which I analyze here.

effective non-labor income, $A+r(h_C)$, and his effective time available, $T-h_C$. I elaborate on this point more fully below.

Define the consumer's reservation wage as $w^* \equiv m(0,A,T)$, that is, as his MRS evaluated at the point where all of his time is allocated to leisure. The necessary condition for working is $w > w^*$, that is, the market wage must exceed the consumer's reservation wage. Likewise, a necessary condition for committing crime is $r'(0) > w^*$, which says that the returns to the first hour of crime must exceed the reservation wage.

A consumer who both commits crime and works on the market--as does the great majority of criminals in the sample--chooses optimal criminal hours to satisfy $r'(h_c) = w$, that is, to set the marginal returns to crime equal to the market wage. This condition has two important implications. First, the consumers' problem has a recursive structure. The consumer can be thought of as first deciding how much crime to commit, and then deciding how much time to spend working on the market.[5] This separation result is a well-known feature of the Gronau model (see, e.g., Singh, Squire, and Strauss 1986). Second, the consumer's optimal crime choice involves only $r(h_c)$ and w. That is, tastes play no role in determining how much crime to commit. On the one hand, this condition may seem restrictive. On the other, however, it is a great help in the empirical work. Without such guidance from theory, it would be difficult to defend any exclusion restrictions which are needed to identify the model.

From the first order condition for optimal crime, one can infer a crime participation rule for criminals who work. By the concavity of $r(h_c)$ and the assumption of diminishing marginal utility, a necessary condition for the consumer to commit crime and participate in the labor market is $r'(0) > w$. That is, for all individuals who both work and commit crime, the returns to the first hour of crime must exceed the wage. This crime participation rule

5 This separation of the consumer's problem is logical, not temporal. Both the crime and labor supply decisions are made in the same (single) period.

stems from the amorality assumption, and is central to the estimation strategy developed in the next section.

As mentioned above, the consumer's optimal crime choice affects his market labor supply. Workers for whom $r'(0) \leq w$ commit no crime, setting $h_c = 0$. Optimal labor supply is then chosen in the usual way, by equating the MRS to the wage, so $w = m(h_m, A, T)$. For criminals, on the other hand, the crime choice has two effects: crime increases effective non-labor income from A to $A + r(h_c)$, and decreases the maximum time available for leisure from T to $T - h_c$. To choose optimal market hours, the consumer accounts for his greater effective income and reduced effective time in equating his MRS to his wage. That is, he chooses h_m to satisfy $w = m(h_m, A+r(h_c), T-h_c)$.

Figure 1 illustrates the consumer's problem for two consumers who work on the market. Consumers A and B both face the same wage, given by (minus) the slope of the usual budget line, and both have non-labor income A. Returns to crime, however, given by $r(h_c)$, differ between the two consumers.

For consumer A, returns to crime are fairly lucrative. In particular, the return to the first hour of crime, given by the slope of $r(h_c)$ at T hours of leisure, or equivalently at zero hours of crime, is greater than the market wage. As a result, consumer A commits crime, setting h_c to equate his marginal returns to crime with his market wage. Now with effective non-labor income of $A+r(h_c)$ and effective time available of $T-h_c$, he chooses his optimal labor supply to satisfy $w = m(h_m, A+r(h_c), T-h_c)$.

For consumer B, on the other hand, the returns to crime are low. Since the returns to his first hour of crime are less than his wage, he forsakes crime, setting $h_c = 0$. He chooses market hours h_m to equate his marginal rate of substitution with his wage, satisfying $w = m(h_m, A, T)$.

This simple version of the Gronau model has two main virtues as a model of criminal behavior. First, it is capable of capturing the fact that most criminals work on the labor market. Second, it can be estimated from the relatively limited data at my disposal.

This is because the crime participation rule involves a simple comparison of marginal magnitudes, the return to the first hour of crime and the wage.

In spite of these practical virtues, however, one might criticize the model for failing to incorporate various elements of the environment facing young workers. As mentioned above, the model abstracts from both uncertainty and morality. Likewise, it ignores the possibility that there may be fixed costs associated with committing crime. Nor does it account for involuntary un- or under-employment, which may affect young workers if the minimum wage is binding.

In principle, Gronau's basic model could be extended to incorporate all of these additional features. In fact, some of these extensions would leave at least some of the model's central predictions unchanged. The prediction that higher wages lead to less crime, for example, would hold even after allowing for certain forms of uncertainty, morality, and fixed costs.

The problem with pursuing these extensions is purely practical. Under virtually any extension, the crime participation decision is no longer based on a simple marginal comparison. With fixed costs, for example, the consumer will commit crime only if the returns to crime are higher than the shadow value of leisure by an amount that reflects the fixed costs of committing crime. To estimate such a model credibly would require data on fixed costs, or at least the factors that determine them. Other extensions would require data on criminal returns and criminal hours. Presently I am unaware of any survey that provides reliable information on such detailed measures of crime.

The strategy I pursue in the absence of such information is to estimate the simpler model for which all needed data are available. I then test the model in various ways, including formal over-identification tests. If the principal estimation results are robust to changes in the specification, then one might have a reasonable level of confidence in their validity. At the same time, failures of the specification tests point to areas where further work is needed.

III. ESTIMATION

For estimation purposes, the Gronau model can be described by three equations: a market wage function, a function defining the returns to crime in terms of criminal labor supply, and a function relating the marginal rate of substitution to market labor supply, effective non-labor income, and effective time available. Rather than specifying the model in terms of criminal returns $r(h_c)$ directly, however, I specify the marginal returns to crime $r'(h_c)$. Formulating the model in terms of $r'(h_c)$ enables me to exploit the criminal participation rule from the conceptual model.

I adopt a conventional semi-logarithmic specification for the wage equation. I also assume that the logarithm of marginal criminal returns is linear in criminal hours. Assuming a semi-log specification for the consumer's MRS as well yields the three-equation model given by:

$$ln\ w = X_1\beta_1 + u_1 \tag{1}$$

$$ln\ r'(h_c) = X_2\beta_2 - \alpha_2 h_c + u_2 \tag{2}$$

$$\ln m(h_m, A + r(h_c), T - h_c) = X_3\gamma_{31} + \gamma_{32}h_m + \gamma_{33}[A + r(h_c)] + \gamma_{34}[T - h_c] + u_3. \tag{3}$$

The variables u_1, u_2 and u_3 are normally distributed, zero-mean disturbance terms with variances σ_i^2 and covariances σ_{ij}.[6] The terms X_1, X_2, and X_3 are vectors of exogenous characteristics influencing the three dependent variables. I postpone discussing the variables included in X_1, X_2, and X_3 until the next section, after I describe the data. For now, I discuss how I estimate each equation.

A. The Wage Equation

Consider first the wage equation (1). If everyone in the sample worked, then the wage equation could be estimated by ordinary least squares. Because the sample includes

[6] Note that the MRS can be written as a function of $A+r(h_c)$ and T-h_c for both criminals and non-criminals, since for non-criminals, $h_c = r(h_c) = 0$.

some non-workers, however, the potential for self-selection bias exists (Heckman 1979). From the discussion above, we know that for individuals who choose to work, that is, for whom $h_m > 0$, the market wage w exceeds the reservation wage w*. Thus the probability of employment can be written as

$$
\begin{aligned}
P(h_m > 0) &= P(w > w^*) \\
&= P\left[\frac{u_1 - u_3}{\omega_1} > \frac{-(X_1\beta_1 - X_3\gamma_{31} - \gamma_{33}A - \gamma_{34}T)}{\omega_1}\right] \\
&= \Phi(\varepsilon_1 > -Z_1\delta_1) \qquad (4)
\end{aligned}
$$

defining the terms ε_1 and $Z_1\delta_1$, where $\omega_1^2 = \text{var}(u_1 - u_3)$ and Φ is the standard normal cdf.

Equation (4) defines a reduced-form employment probit that can be used to solve the self-selection problem. Evaluating the expectation of the disturbance term in the wage equation conditional on employment yields

$$
\begin{aligned}
E(u_1 \mid w > w^*) &= E(u_1 \mid \varepsilon_1 > -Z_1\delta_1) \\
&= \sigma_1\rho_{11}\lambda_1(Z_1\delta_1)
\end{aligned}
$$

where $\rho_{11} = corr(u_1, \varepsilon_1)$, $\lambda_1(z) = \phi(z) / \Phi(z)$, and ϕ is the standard normal pdf. To account for self-selection into employment in estimating the wage equation, I fit

$$
\ln w = X_1\beta_1 + \sigma_1\rho_{11}\lambda\left(Z_1\hat{\delta}_1\right) + v_1 \qquad (5)
$$

where $\hat{\delta}_1$ is the vector of estimated coefficients from the reduced-form employment probit, and v_1 is a zero-mean disturbance term.

B. The Crime Participation Function

Consider next the marginal returns to crime equation (2). The main problem here is that criminal hours h_c are unobserved. Nevertheless, the parameters of the determinants of criminal returns, β_2, can be estimated by exploiting the crime participation rule from the Gronau model.

Denote the crime participation dummy summarized in Table 1 by C. The crime participation rule says that, for workers, if $C = 1$, then the returns to the first hour of crime exceed the wage. In other words, $r'(0) > w$. This motivates an estimating equation, since I can write:

$$\begin{aligned} P(C = 1) &= P(\ln r'(0) - \ln w > 0) \\ &= P[\frac{u_2}{\sigma_2} > -(X_2\beta_2 - \ln w)/\sigma_2]. \end{aligned} \tag{6}$$

Because equation (6) includes ln w, an endogenous regressor, I will refer to it as a structural crime participation function. In addition to endogeneity, the presence of the log wage as a regressor raises a second estimation issue: wages are observed only for workers. Both of these problems could be solved by replacing ln w with predicted values from the estimated wage equation, and estimating equation (6) by the probit method.

A more efficient method is given by Amemiya (1978), however. To apply Amemiya's technique, one first estimates a reduced-form crime probit, and then uses the generalized method of moments to solve for the structural parameters $\theta_2 \equiv (\beta_2/\sigma_2, -1/\sigma_2)$ in terms of the reduced form parameters.

From the model, the necessary condition for committing crime is that $r'(0) > w^*$. Thus the reduced-form crime probit takes the form

$$\begin{aligned} P(C = 1) &= P(r'(0) > w^*) \\ &= P\left[\frac{u_2 - u_3}{\omega_2} > \frac{-(X_2\beta_2 - X_3\gamma_{31} - \gamma_{33}A - \gamma_{34}T)}{\omega_2}\right] \\ &= \Phi(\varepsilon_2 > -Z_2\delta_2) \end{aligned}$$

defining the terms ε_2 and $Z_2\delta_2$, where $\omega_2^2 = \text{var}(u_2 - u_3)$.

To obtain the GMM estimates, write the relationship between θ_2 and δ_2 as

$\delta_2 = f(\theta_2)$, and choose $\hat{\theta}_2$ to solve $\min[\hat{\delta}_2 - f(\theta_2)]'\hat{W}[\hat{\delta}_2 - f(\theta_2)]$ where $\hat{\delta}_2$ is the vector of estimated coefficients from the reduced-form crime probit and $\hat{W}$ is a consistent estimate of the inverse covariance matrix of $[\hat{\delta}_2 - f(\theta_2)]$. In addition to providing efficient estimates, the GMM approach has an additional advantage. Under the null hypothesis that the identifying exclusion restrictions are correct, the quadratic form $[\hat{\delta}_2 - f(\hat{\theta}_2)]'\hat{W}[\hat{\delta}_2 - f(\hat{\theta}_2)]$ is asymptotically chi-square with degrees of freedom equal to the number of exclusion restrictions. Thus the procedure provides a means for testing the overidentifying restrictions on which the structural parameter estimates are based (Newey 1985).[7]

C. The Consumer's MRS

Consider next equation (3), the MRS function. A problem once again is that, in general, h_c is unobserved. Another problem is that, for non-workers, the consumer's first-order conditions for optimal labor supply cannot be used to replace the unobserved MRS with the observed wage.

The solution to these problems is to obtain estimates from the sample of working non-criminals, for whom all necessary data are observed. For working non-criminals, we have $h_c = r(h_c) = 0$ and $\ln m(h_m, A, T) = \ln w$. Solving equation (3) for market hours thus yields a conventional-looking labor supply function:

$$h_m = X_3\beta_{31} + \beta_{32}\ln w + \beta_{33}A + \eta \qquad (7)$$

where $\beta_{31} = -\gamma_{31}/\gamma_{32}$, $\beta_{32} = 1/\gamma_{32}$, $\beta_{33} = -\gamma_{33}/\gamma_{32}$, and $\eta = -u_3/\gamma_{32}$. I have implicitly subsumed the term $\beta_{34}T$, which does not vary across individuals, in the constant term.

7 Amemiya and Maddala (1983, ch. 8) provide explicit expressions for $f(\theta_2)$, $\hat{W}$, and the asymptotic covariance of $\hat{\theta}_2$.

Equation (7) still poses two estimation problems: self-selection and the endogeneity of $\ln w$. To solve the self-selection problem, I must evaluate the expectation of the disturbance term η conditional on working and not committing crime, for which the reduced form crime probit defined above will be helpful. In general, evaluating a bivariate selection term such as $E[\eta | w > w^*, r'(0) \leq w^*]$ involves some complicated algebra. The algebra simplifies tremendously, however, when the two conditioning events are independent (Fishe, Trost, and Lurie 1981). Table 1 suggests that the decision of whether to work is indeed independent of the decision to commit crime.[8]

Under independence, we have

$$\begin{aligned} E[\eta | w > w^*, r'(0) \leq w^*] &= E[\eta | \varepsilon_1 > -Z_1\delta_1, \varepsilon_2 \leq -Z_2\delta_2] \\ &= \sigma_\eta \tau_{\eta 1} \lambda_1(Z_1\delta_1) + \sigma_\eta \tau_{\eta 2} \lambda_2(Z_2\delta_2) \end{aligned}$$

where $\sigma_\eta^2 = \mathrm{var}(\eta)$ and $\tau_{\eta i} = corr(\eta, \varepsilon_i)$. The first term on the RHS of this expression accounts for self-selection into employment, whereas the second term accounts for self-selection *out* of crime. The λ functions can be estimated from the reduced-form employment probit and the reduced-form crime probit, and then included in the labor supply equation.

To account for endogenous wages, I replace actual log wages $\ln w$ with fitted values $\widehat{\ln w}$.[9] Thus the estimating equation for the labor supply function to be fit to the sample of working non-criminals is:

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8 This bivariate evidence is supported by a more formal analysis as well. In preliminary work, I fit a joint reduced-form employment/reduced-form crime participation model as a bivariate probit. The estimated correlation between ε_1 and ε_2 was -0.03, with a standard error of 0.13.

9 The fitted values must incorporate the sample selection corrections. The appropriate expression is $\widehat{\ln w} = X_1\hat{\beta}_1 + \hat{\sigma_1 \rho_{11}} \lambda_1(Z_1\hat{\delta}_1) + \hat{\sigma_1 \rho_{12}} \lambda_2(Z_2\hat{\delta}_2)$, where $\rho_{12} = corr(u_1, \varepsilon_2)$. The parameter $\sigma_1\rho_{12}$ is estimated as the coefficient on $\lambda_2(Z_2\hat{\delta}_2)$ in an auxiliary regression of $\ln w$ on X_1, $\lambda_2(Z_2\hat{\delta}_2)$, and $\lambda_2(Z_2\hat{\delta}_2)$ that is restricted to the sample of working non-criminals.

$$h_m = X_3\beta_3 + \beta_{32}\ln \hat{w} + \beta_{33}A + \sigma_{\eta}\tau_{\eta 1}\lambda_1(Z_1\hat{\delta}_1) + \sigma_{\eta}\tau_{\eta 2}\lambda_2(Z_2\hat{\delta}_2) + v_2 \qquad (8)$$

where v_2 is a zero-mean disturbance term.[10]

IV. THE DATA AND MODEL SPECIFICATION

A. General

The data are taken from the NLSY. This panel study was initiated in 1979 as a survey of youths 14 to 21 years old, and includes a nationally representative sample as well as an over-sampling of minority and disadvantaged youths. I use data from the full sample, without sampling weights, in the empirical analysis.[11]

In 1980, the usual survey questionnaire was augmented by a special module that asked respondents whether they committed several specific types of crimes during 1979, and what fraction of their income was derived from crime. The module also included questions about arrests and court proceedings both during and before 1979. Unfortunately, the crime module was administered only once; longitudinal data on crime therefore are not available from the survey. With a few exceptions noted below, the data I analyze are from the 1980 wave of data collection.

Since men are responsible for the vast majority of crimes committed, I exclude women from the analysis. I also exclude men who were enrolled in school or enlisted in the military in 1979, 1980, or 1981. The purpose of this restriction is to limit the sample to men who had permanently left school, and whose primary alternatives to leisure would have been market work or crime. I also exclude respondents who were interviewed in jail in 1979 or 1980, or who indicated that they had been released from jail during those years.

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10 I derive the covariance matrix for the parameters of the labor supply function in Appendix A.

11 Weighted estimates are very similar to the unweighted estimates.

B. Measuring Crime

Table 2 lists all the items from the 1980 crime questionnaire that potentially involve property crimes. Column (1) reports participation rates tabulated from the estimation sample. It is evident that many young men commit such low-level crimes as shoplifting and other low-value thefts. Drug dealing, con games, and trade in stolen goods likewise are fairly common. Taken together, 54 percent of the sample committed at least one potential property crime.

As first seen in Table 1, however, and reiterated in the last row of Table 2, 24 percent of the sample earned income from crime. A natural question to ask is why only 24 percent of the sample reported income from crime when 54 percent admitted to committing a crime that could have earned them some money. One reason is that several of the specific crime questions are broad enough to include not only true property crimes, but also other activities whose motives are not acquisitive in nature. For example, the question about taking someone's car could pertain to an actual car theft or simply to taking one's parents' car without permission. Likewise, breaking into a building may be a prelude to a burglary, but the ethnographical criminology literature also contains many accounts of youths entering vacant houses in order to drink, take drugs, or just "hang out" (Sullivan 1989).

Furthermore, not all crimes are actually rewarded. For example, con games only yield income if the ploy is successful. Likewise, merely holding stolen goods may have no payoff. In summary, it is safe to say that there are many reasons why participation rates based on the specific crime questions may differ legitimately from participation rates based on the question about criminal income. The advantage of the income-based measure is that it is concrete in the sense that it indicates that at least one crime occurred for which the perpetrator actually received a monetary reward.

The income-based measure has a second important advantage as well: it appears to have greater validity than the measure derived from the specific crime questions. There are obvious incentive problems in collecting self-reported data on crime, and one manifestation of such incentive problems has been extensively studied. In most self-reported crime surveys, participation rates for young black men are about the same as participation rates for young white men. Police arrest records, in contrast, generally show substantially higher participation rates for blacks (Elliott and Huizinga 1980; Hindelang, Hirschi, and Weis 1981). This discrepancy has been analyzed at length by Hindelang, Hirschi, and Weis (1981), who collected both self-report data and police arrest records for a random sample of individuals. Based on cross-checks between self reports and police records, they concluded that young black men generally understate the amount of crime they commit by a substantial amount.

This apparent understatement is reflected in the specific crime questions in the NLSY crime module, as seen in the second column of Table 2. Although there are exceptions, the black/white participation ratio for most of the questions ranges from 0.75 to 1.25. For property crimes as a whole, the participation ratio is 1.03. These low participation ratios call the validity of the specific crime items into question.

In contrast, the participation ratio from the income-based measure is 1.52. This is much higher than the ratio from the specific crime questions, and close to the estimate of 1.7 from Wolfgang, et al's (1972) study of police records. Thus based on this important and widely-studied measure. I conclude that the crime participation dummy derived from the question about criminal income has greater validity than the participation variable based on the specific crime questions. The remainder of the analysis thus utilizes the income-based crime participation dummy.[12]

As discussed in the previous section, my estimation approach also requires a measure of effective non-labor income $A + r(h_c)$, and hence a measure of criminal income $r(h_c)$. For the question about income from crime, survey respondents were asked what fraction of their 1979 income came from crime. The possible response categories were: none, "very little", about one-fourth, about one-half, about three-fourths, or "almost all". I multiply this reported fraction by the respondent's 1979 income (from all sources) to obtain my criminal income measure.[13] Among criminals, mean criminal income was $1188. This corresponds fairly well to information from other surveys. Freeman (1991), for example, reports that among criminals in the 1980 NBER Inner City Youth Survey, mean criminal income was $1607.

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[12] Estimates based on the participation dummy derived from the flawed specific crime data show that higher wages lead to more crime, a finding that would be difficult to reconcile with almost any economic model. Data quality is very important in this study.

[13] I took "very little" to mean 10 percent, and "almost all" to mean 90 percent. The results are not particularly sensitive to these specific choices, however.

C. Labor Market Data

Since the crime variables pertain to crimes committed over the period of a year, it is natural to choose an annual measure of market labor supply. I use the number of hours worked in 1979, then construct an hourly wage by dividing 1979 earnings by 1979 hours. Preliminary analyses using weeks worked in 1979 and weekly wages gave substantially similar results. Mean market hours and log wages are reported in Table 3. As one might expect, criminals work less and earn lower wages than non-criminals.

D. Explanatory Variables and Model Specification

The wage equation is easy to specify, because a large body of both theory and previous empirical work provide guidance. I include three human capital measures: years of education, a high school graduation dummy, and years of potential labor market experience. I also include the AFQT score as a measure of ability, and dummies for union membership, race, ethnicity, urban location, and marital status.[14] The only unusual variables to appear in the wage equation are two indicators of recent contact with the criminal justice system. The first dummy variable takes on the value of one if the respondent was charged with or convicted of a crime during the sample period, and the second equals one if the respondent was on probation during 1979. I include these variables on the basis of my earlier results that arrests and probation sentences have short-lasting but statistically significant effects on the earnings of arrestees (Grogger 1995).

Deciding which variables to include in the structural crime probit requires greater reflection. Fortunately, the Gronau model provides at least some guidance. In the model, criminal participation is not affected by tastes. Rather, the first line of equation (6) indicates that the structural crime probit should include only the market wage and variables

[14] I adjusted the AFQT to remove the effects of race and the age of the respondent at the time the test was administered. Using the full sample of males, I regressed the raw AFQT scores on race dummies and a full set of age dummies. The adjusted AFQT measure here consists of the residuals from this regression.

that affect the individual's productivity in crime, that is, variables that affect $r'(0)$. Thus in principle at least, the model provides some exclusion restrictions. In practice, however, the problem remains that the determinants of criminal productivity are largely unknown. To my knowledge, there has been no research in this area.

It seems reasonable to posit, however, that a consumer's criminal productivity would be determined by his criminal human capital much in the way that his market productivity is affected by his market human capital. Extending the analogy a bit further suggests that the sum of past criminal experience may provide a valuable measure of current criminal human capital, much as the sum of past work experience provides an important measure of current market human capital. Unlike past work experience, however, past criminal experience is difficult to measure accurately. Indeed the only measures of past crime available in the NLSY are rather coarse proxies for past criminal experience. I include two such variables in the structural crime probit: a dummy equal to one if the respondent reported being charged with or convicted of a crime at some point prior to the sample period, and another dummy equal to one if he had ever been sentenced to probation prior to the sample period.[15] These variables provide measures--albeit laden with error--of past criminal experience.

I also include a third criminal human capital dummy that is equal to one if the respondent had a brother who had ever been charged with, convicted of, or sentenced for a crime as of 1980, or who, at any time between 1979 and 1991, was interviewed in jail. The notion here is that having a brother who himself is a criminal may contribute to one's own criminal productivity by providing information on criminal techniques, potential targets, or police activity. This measure is available because the NLSY originally surveyed households, and included in the survey all 14- to 21-year-olds residing in each household.

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[15] It would seem natural to include an indicator of pre-sample period jail spells as well. None of the sample members reported serving any time in jail prior to 1979, however.

Because only about 30 percent of the sample had a brother who was also included in the study, I also include as a statistical control a dummy variable equal to one if the respondent had no brothers in the survey.

Finally, I include dummies for urban location, race, and ethnicity. Urban location may affect one's productivity in crime since, all else equal, potential criminal targets are more numerous in central cities than in suburban or rural areas. The race and ethnicity dummies are included to test for whether the model is capable of explaining the demographic differentials in crime rates.

In specifying the market labor supply function, previous research provides some guidance. I include the (predicted) log of the market wage, non-labor income, and the two sample selection terms described above. I also include the dummies reflecting race, ethnicity, and urban location.

This preliminary specification of the model draws on theory and previous work wherever possible. Nevertheless, one might argue that the resulting specification, and implicitly the identifying exclusion restrictions, reflect a number of fairly arbitrary choices. Ultimately, of course, identification requires some exclusion restrictions: it is impossible to be completely agnostic in estimating a system of simultaneous equations.

Fortunately, however, the specification can be tested, because the model is substantially over-identified. Tests of the over-identifying restrictions can be used to provide a check on the validity of the specification. Where necessary, moreover, I can amend the specification in ways suggested by the over-identification tests, and assess the robustness of my main results to changes in the exclusion restrictions.

V. RESULTS

A. Market Wages

Consider first the market wage function. OLS estimates of equation (5) are presented in Table 4. In general, the results are similar to those from other wage studies. The returns to education are particularly high, however, which may be attributable to the rather low educational attainment of the sample. Wages rise quickly with experience, again likely due to the youthfulness of the sample members. The ability and union coefficients are positive and significant. The signs and magnitudes of the demographic indicators are typical.

The coefficient of the arrest dummy shows that individuals who were charged with or convicted of a crime during 1979 had wages that were 15 percent lower on average than those of other individuals. Being on probation during the sample period reduced wages by 29 percent on average. These results are generally consistent with the findings from my earlier paper (Grogger 1995).

Moreover, the negative effect of probation on wages has an interesting economic interpretation. Employment is often stipulated as a condition of probation. In general, the punishment for violating such conditions is that probation is revoked, and the probationer serves the rest of his sentence in jail. Therefore, if freedom is valuable, then the typical probationer should be willing to work for lower wages than an otherwise identical agent who is not subject to the terms of probation.

I attempted to test the hypothesis that committing crime during the sample period affects market wages. In the context of the theoretical model, it is not entirely clear how one should carry out such a test, although it is clear the model would come into question if the test were to reject. I carried out three separate tests, each time including a different measure of current criminal participation in the wage equation. When I included the crime dummy C, its coefficient (standard error) was 0.003 (0.047). When I included the predicted probability of committing crime from the reduced-form crime probit, the coefficient was 0.106 (0.335). When I included the predicted "index" from the reduced-form crime probit, $Z_2\hat{\delta}_2$, I obtained 0.102 (0.115). I conclude that there is little evidence that current participation in crime affects young men's wages.

I also tested whether the criminal human capital variables could be excluded legitimately from the wage equation. When I added the variables reflecting past arrests and convictions, past sentences, and whether the respondent's brother was a criminal, none of the coefficients was even marginally significant. Indeed all of the coefficients were smaller than their standard errors. The F-statistic for the joint test was 0.24, well below the mean for an F-statistic with three numerator degrees of freedom. Furthermore, adding these variables had no discernible effect on the other coefficients in the model. These results support the notion that my criminal human capital measures fail to explain wages. They also are consistent with my earlier findings, based on a different set of data and derived using a different statistical approach, that arrests and convictions have only short-lasting effects on criminals' market earnings (Grogger 1995).

B. The Structural Crime Probit

Consider next the estimates of the structural crime probit in column (1) of Table 5. The effect of wages on criminal participation, displayed in the first row, is negative and quite significant. The average partial derivative of the probability of committing crime with respect to the log wage is -0.178. This indicates that a ten percent increase in wages would reduce the criminal participation rate by 1.8 percentage points. Participation in crime by young men is thus quite responsive to wages. This finding raises the possibility that the rise in youth crime over the past two decades may have resulted, at least in part, from the decline in real wages. I return to this topic below.

The remaining coefficients can be interpreted as showing how criminal human capital and other individual characteristics affect the consumer's marginal returns to crime, or equivalently, his choice to commit crime. The criminal human capital variables are positive and significant. Past criminal experience, as measured either by past arrests and convictions or by past probation spells, raises current criminal productivity. This suggests that criminals may learn by doing much in the way that workers learn on the job. It also suggests that crime may be a self-reinforcing activity. As the consumer commits more crime, he becomes a more productive criminal, encouraging him in turn to commit still more crime.

The brother variable is also positive and at least marginally significant. Having a brother who is himself a criminal may be a good way to learn the trade. Put differently, crime appears to run in families.

The over-identification statistic at the bottom of the table suggests that the conclusions drawn from this model may be suspect, however, because the over-identifying restrictions on which the estimates are based are rejected. Some investigation revealed that the rejection resulted from excluding the union dummy and the 1979 charged-or-convicted dummy from the model. The estimates in columns (2) through (4) are from specifications that include those variables.

In column (2) we see that, when entered by itself, the union dummy is positive and significant, suggesting that on average, union members are more productive criminals. Adding the union dummy to the model reduces the wage coefficient slightly. This amended specification still fails the over-identification test, however.

In the next column, the dummy for 1979 arrests and convictions is included in the model. Its coefficient is also positive and significant. The wage coefficient is about the same as in the previous specification. The over-identification test narrowly fails to reject at the 5 percent level.

Finally, column (4) reports estimates from a specification that includes both variables. Both coefficients are significant. The wage coefficient is now slightly larger than the original estimate in column (1). The over-identification test now passes at a comfortable level.

Thus the original specification of the model is rejected by the over-identification tests. Should this lead one to reject the Gronau model more broadly as a description of how youths allocate their time between work and crime? I believe that such a conclusion would be premature. In the first place, the union effect may reflect criminal productivity differentials. The average union workplace is larger the average non-union shop, and union workers generally earn more than non-union workers. This may facilitate such crimes as drug dealing and gambling rackets.

Indeed the data on specific crimes provide some support for this notion. In Table 6 I present union/non-union participation ratios for the various economic crimes included in the NLSY crime questionnaire. Although these data may provide a poor indicator of the level of crime committed by young men, they nevertheless may provide a reasonable indicator of relative participation rates provided that reporting problems are comparable across union and non-union workers.

The data in Table 6 show that in general, union workers commit about 1.2 times as many crimes as their non-union counterparts. Union workers are most heavily over-represented in selling hard drugs and gambling, two crimes that may be facilitated by working in larger shops with richer coworkers.[16] Because union workers are also more involved in other crimes where the union environment offers little advantage, this evidence is not decisive. Nevertheless, it is supportive of the notion that union workers commit more property crimes in part because unionized environments make them more productive. Therefore I conclude that the significant union effect does not by itself provide a compelling reason for dismissing the Gronau model.

The coefficient of the current arrest variable is harder to interpret. Its significance suggests that persistence in criminal behavior is not fully captured by wages. On the one

16 Ideally, one would like to know whether the crimes were committed at the workplace. Unfortunately, the NLSY contains no information on when or where the crimes were committed.

hand, this may indicate that tastes indeed matter, which would call into question the simple version of the Gronau model presented in section II. On the other hand, the significant coefficient on current arrests simply may be the result of measurement error in the criminal experience variables. That is, even if current arrests have no effect on criminal returns conditional on actual criminal experience, they may appear significant if criminal experience is poorly measured and current arrests are correlated with past criminal experience, as seems likely.

These two competing explanations for the significant current arrest coefficient have quite different implications for the validity of the simple Gronau model. With good data on criminal experience, it would be straightforward to sort them out. Without good data, however, it is unclear whether the significant current arrest coefficient represents a failure of the theoretical model or whether it reflects the coarseness of my measures of past criminal experience.

In the face of such ambiguity, a key question is whether adding current arrests to the model has important implications for the substantive results. Comparing the estimated wage coefficients across the various specifications in Table 5 suggests not. The smallest wage coefficient indicates that, in response to a 10 percent decline in wages, participation in crime would rise by 1.5 percentage points. The largest coefficient would lead one to predict a 2 percentage point increase. Put differently, the estimates of the elasticity of criminal participation with respect to market wages range from -0.61 to -0.89. The estimates of the other coefficients vary even less.

The results in Table 7 reinforce this point further. Here I present estimates from alternative specifications that explicitly relax a number of the remaining over-identifying restrictions. In addition to the variables shown, all regressions include all variables present in column (4) of Table 5. Because the criminal human capital coefficients and the union coefficients vary so little, I suppress them here in order to save space.

In the first column I include the three market human capital variables in the structural crime probit. The signs of the coefficients are mixed. Taken at face value, the estimates indicate that additional years of education contribute to criminal productivity, although graduating from high school reduces it. Only the graduation coefficient is even marginally significant, however. The Wald chi-square statistic to test the joint significance of all three variables is 4.21, which fails to reject at the 10 percent level. The remaining columns similarly support the exclusion of the income, AFQT, and marital status variables.

These additional estimation results also may help in determining why the current arrest variable is significant in the structural crime probit. If excluded tastes were the reason, then one would expect these additional variables to be significant as well, since tastes for education and marriage likely would be negatively correlated with tastes for crime. Moreover, if the current arrest indicator were merely picking up excluded tastes for crime, then adding the additional regressors should change the coefficient on the current arrest variable. Instead, the additional regressors are insignificant at conventional levels, and the current arrest coefficient is essentially invariant across the various specifications. Thus the results in Table 7 provide indirect evidence against the hypothesis that omitted tastes are responsible for the significant coefficient on current arrests. Presumably, they also provide evidence in favor of the hypothesis that the significant coefficient is the result of measurement error in the criminal experience measure.

The most important point to be taken from Table 7, however, is that the estimates of the wage coefficient are largely robust to these changes in the specification. Although the simplest model is rejected by the formal specification tests, the alternative specifications that pass the tests yield very similar results.

Collectively, the estimates from Tables 5 and 7 suggest several conclusions. First, although the market wage and criminal human capital variables perform as expected, the initial specification of the structural crime probit is statistically inadequate. This suggests that there is more to be learned about the determinants of criminal productivity. In particular, better measures of young men's previous criminal experience would be quite valuable for future research.

Nevertheless, even though the initial model is formally rejected, the main results are robust to changes in the specification. They indicate that young men are quite responsive to price incentives. A ten percent increase in wages would reduce youth participation in crime by roughly 6 to 9 percent.

C. Market Labor Supply

The last equation in the model is the market labor supply function, estimates of which are reported in column (1) of Table 8. The effect of wages on market hours is large. On average, a ten percent increase in wages leads to an increase in labor supply of 61 hours, the equivalent of one -and-a-half full-time work weeks. At mean labor supply of 1693 hours per year, this implies an elasticity of 0.36. This is somewhat higher than most estimates for males, which is probably reasonable given the lesser labor force attachment of young men. This result reinforces the basic point that young men's behavior is responsive to wage incentives.

The income effect is small and at best marginally significant, but is negative as theory requires. The selectivity coefficients are both positive, but only the coefficient of the crime selection term is significant. The implication is that failing to account for youth crime may result in a misspecification of the labor supply equation.

The results in the second column of the table make this point more explicitly. Here I present estimates of a labor supply function that neglects crime altogether. All information about crime has been excluded both from the wage equation used to predict wages and from the labor supply function itself. With no information on crime, a researcher presumably would use all the workers in the sample to estimate the model. For this reason, the estimates in column (2) are based on all 1075 respondents who reported working in the previous year.

The wage coefficient from this naive model is 731.7. This is 20 percent larger than the estimate from column (1), which incorporates the information about crime. Thus a substantial fraction of the apparent wage responsiveness of young men in the naive model is attributable to their outside opportunities in crime.

Suppose alternatively that the researcher knew who committed crime, but had no information about criminal human capital. Although the researcher would not be able to estimate the formal selection model, he or she might exclude the criminals from the estimation sample in the hope of lessening the bias that arises from neglecting the problem altogether. The question is whether this expedient but informal fix actually would yield better estimates.

The results from this exercise are presented in the third column of Table 8. The wage coefficient is a bit smaller than the estimate in column (2), but the difference is slight. The wage parameter is still 16 percent too high. Failing to account properly for youth crime leads one to over-estimate the elasticity of youth labor supply with respect to the wage by a fair amount.

D. Wages and the Black-White Crime Differential

I now ask whether the black-white wage gap can explain the racial differential in criminal participation rates. The estimates in Table 5 suggest that, as a whole, the model indeed explains a part of the racial crime gap. A simple probit regression of the crime indicator on the black and Hispanic dummies, with no other regressors, yielded a black coefficient of 0.408 (0.102). In contrast, the black coefficients in the structural crime probits in Table 5 are only about one-half as large.

To measure the contribution of wages, I performed a Oaxaca-type decomposition based on the specification in column (4) of Table 5. The first step of this exercise involves estimating the structural crime probit separately by race. Denote the predicted values from these models by $P(\ln w^j, X_2^j; \hat{\theta}_2^j)$, where $j = w, b$ denotes data and estimates from the white and black subsamples, respectively.[17] The difference in crime participation rates between blacks and whites can be written as

$$P(\ln w^w, X_2^w; \hat{\theta}_2^w) - P(\ln w^b, X_2^b; \hat{\theta}_2^b) = [P(\ln w^w, X_2^w; \hat{\theta}_2^w) - P(\ln w^b, X_2^b; \hat{\theta}_2^w)] \\ +[P(\ln w^b, X_2^b; \hat{\theta}_2^w) - P(\ln w^b, X_2^b; \hat{\theta}_2^b)]$$

The first term in brackets gives the component of the difference in the outcome that can be attributed to differences in market wages and the other regressors in the model; the second term in brackets gives the component attributable to difference in the race-specific regression coefficients. This step of the exercise showed that 7.3 percentage points of the 13.7 percentage differential in crime participation rates is attributable to differences in wages and the other regressors.

To isolate the effect of wages, I equalized mean wages, recalculating the decomposition after adding the mean black-white wage differential (Δ) to the wage of each black in the sample. The resulting quantity, $P(\ln w^w, X_2^w; \hat{\theta}_2^w) - P(\ln w^b + \Delta, X_2^b; \hat{\theta}_2^w)$, accounted for only 2.3 percentage points of the racial differential in crime rates. In other words, the black-white wage gap explains 5.0 percentage points, or 36 percent, of the racial differential in crime participation rates.

E. Do Falling Wages Account for the Time-Series Changes in Youth Behavior?

In light of the substantial body of research on recent changes in the wage distribution, it is particularly interesting to ask whether rising youth crime is a result, at least in part, of falling youth wages. Since the mid-1970's, real wages paid to men 16-24 years old who work full time have fallen 20.3 percent (Bureau of Labor Statistics 1980, 1989). Real hourly wages paid to male hourly workers between 16 and 24 years old, which

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17 Algebraically, $P(\ln w^j, X_2^j; \hat{\theta}_2^j) = \frac{1}{n_j}\sum_{i=1}^{n_j}\Phi\left[X_{2i}^j(\frac{\hat{\beta}_2}{\sigma_2})^j - (\frac{\hat{1}}{\sigma_2})^j \ln w_i^j\right]$ where the i subscript explicitly denotes individual observations and n_j is the number of observations in group j.

may provide a better gauge of the labor market opportunities facing young, relatively unskilled men, behaved similarly, falling by 23.0 percent.

In response to a 20 percent fall in wages, the model predicts that youth participation in crime should rise by 12 to 18 percent. Unfortunately, data on criminal participation do not exist. The Federal Bureau of Investigation (1990) does publish age-specific arrest rates, however, which may provide at least a rough gauge of trends in participation rates. Between the early 1970's and the late 1980's, arrest rates for 16- to 24-year-old males rose from 44.6 to 52.6 per 1000 population, a gain of 18 percent.

The model also predicts that youth labor supply should fall by 7.4 percent in response to a 20 percent fall in wages. An analysis of the March Demographic Files of the Current Population Survey for the years 1970-74 and 1985-88 shows that among men 16 to 19 years old who were not in school or the military, market hours fell 21 percent. For comparable 20- to 24-year-olds, market labor supply fell 3 percent. The weighted average decrease was 10 percent.

Thus for both youth crime and labor supply, the predictions from the model are close to the actual changes. Perhaps it is not surprising that lower wages lead to less work. The more novel finding is that, among the various other consequences of the recent changes in the wage distribution, the decline in real wages may have been an important determinant of the recent rise in youth crime.

F. Market Wages and the Age Distribution of Crime

As a final application, I use the model to study the age distribution of crime. Numerous researchers have reported that the age-crime profile rises until the late teens, then falls rapidly (Blumstein, Cohen, Roth, and Vischer 1986; Farrington 1986; Gottfredson and Hirschi 1986). This pattern appears to hold over time, across countries, and irrespective of the way crime is measured (Hirschi and Gottfredson 1983).

There recently has been considerable dispute over the causes of the age-crime relationship, however, and even over the value of attempting to explain it (Hirschi and

Gottfredson 1983; Greenberg 1985; Gottfredson and Hirschi 1986; Blumstein, Cohen, and Farrington 1988). On one side of the debate, Greenberg (1985) has offered an explanation based on sociological theory, and Tittle (1980) has attempted to explain the age-crime profile empirically in terms of covariates such as family background and labor market status. On the other side, Hirschi and Gottfredson (1983) have argued that the age effect is "direct" and "invariant", and simply "cannot be accounted for by any ... combination of variables ... currently available to criminology" (p. 554).

To my knowledge, however, none of these researchers has asked whether wages might explain the shape of the age-crime profile. For economists this is a natural hypothesis to consider. Wages measure the opportunity cost of crime, and grow with age as a worker accumulates labor market experience.

Table 9 presents the evidence. The first panel presents actual crime participation rates by age. The NLSY data are no exception to the rule: crime falls sharply during the late teens and early 20's.

The next panel presents predicted participation rates from the four specifications of the structural crime probit reported in Table 5. In all cases, the predictions follow the pattern of the actual data. Considering that neither age nor labor market experience were included in the structural crime probits, the models do a good job at replicating the age distribution of crime.

Do wages explain the pattern? The last panel reports the mean predicted participation rates by age that result when wages are fixed at the sample average. For all four specifications, the steep decrease with age essentially disappears. Instead, participation rates are nearly constant. I conclude that the age distribution of crime is largely a labor market phenomenon: the growth in market opportunities with age is largely responsible for the concomitant decrease in crime.[18]

In principle, it would be interesting to corroborate this finding with data from different countries. Since the age-earnings profile is steeper in some countries than others, the age-crime profile should vary across countries as well. Unfortunately, differences in the way different countries define and measure crime make such comparisons problematic. Farrington (1986) attempted such a comparison between England and the U.S., and concluded that their age-crime relationships were similar. Because there were differences in crime categories (all crimes in England vs. non-violent crimes in the U.S.) and crime measures (arrests in the U.S. vs. convictions and cautions in England) across the two countries, however, it is not clear that one can draw any firm conclusions from his results.

VI. CONCLUSIONS

The primary conclusion from this study is that young men are responsive to wage incentives. This conclusion has a number of implications. First, the racial differential in crime rates is in part a labor market phenomenon. Blacks typically earn less than whites, and this wage gap explains about one-third of the racial difference in criminal participation rates.

Next, decreases in real wages may have played an important role in the increase in youth crime over the past twenty years. Estimates from the model suggest that changes in wages account for at least three-quarters of the observed rise in youth crime.

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[18] Another way to test whether the model explains the age distribution of crime is to include a full set of age dummies in the structural crime probit. When I did this, the age dummies were jointly and individually insignificant, and they had little effect on the other parameter estimates.

Finally, wages largely explain the tendency for crime to decrease with age, a phenomenon widely observed by criminologists. In the context of a time-allocation model, this seems quite reasonable. Wages represent the opportunity cost of crime, and are well-known to rise with age.

Together, these results suggest that the insights of economic theory may be even more useful for understanding crime than has been recognized previously. Nevertheless, it would be desirable to further demonstrate their robustness. Although the estimates presented here are largely insensitive to changes in the econometric specification, that specification is itself based on a fairly restrictive economic model. It would be valuable in future work to allow for extensions such as uncertainty in the returns to crime, fixed costs of committing crime, and labor market rationing due to binding minimum wages. Ideally, the next step would be to collect richer data, and use them to relax the restrictions of the model presented here.

Appendix A: The Covariance Matrix for the Labor Supply Equation

Under the independence assumption, the covariance matrix for the double selection model is a straightforward extension of the covariance matrix for the usual selection model (e.g., Greene 1993, p. 713). In this appendix I modify my notation slightly, using I subscripts to denote individual observations. The corresponding expressions without I subscripts now refer to the data matrix whose typical row is the ith observation.

Rewrite equation (8) more compactly as

$$h_{mi} = S_i\beta + \gamma_1\lambda_{1i} + \gamma_2\lambda_{21} + v_{2i} \qquad (8')$$

where $S_i = [X_{3i}, \hat{\ln w_i}, A_i]$, $\beta = [\beta_3', \beta_{32}, \beta_{33}]$, $\gamma_j = \sigma_\eta \tau_{\eta j}$, and $\lambda_{ji} = \lambda_i(Z_{ji}\delta_j)$. It will suffice to define S_i in terms of $\hat{\ln w_i}$ because all of the other regressors in equation (8') are included in the expression for $\hat{\ln w_i}$. In other words, the predicted values for $\ln w_i$ account for the sample selection corrections, as noted in footnote 9. It will be convenient to write equation (8') even more compactly, as

$$h_{mi} = X_i\theta + v_{2i}, \qquad (8'')$$

where $X_i = [S_i, \lambda_{1i}, \lambda_{2i}]$ and $\theta = [\beta', \gamma_1, \gamma_2]'$.

The error term v_{2i} is heteroskedastic, with variance

$\mathrm{var}(v_{2i}) = \sigma_\eta^2[1 - \tau_{\eta 1}^2\xi_{1i} - \tau_{\eta 2}^2\xi_{2i}]$, where $\sigma_\eta^2 = \mathrm{var}(\eta_i)$ and $\xi_{ji} = \lambda_{ji}(\lambda_{ji} - Z_{ji}\delta_j)$. Define Ξ_j to be the diagonal matrix with the terms ξ_{ji} on the diagonal, and

$Q_j = \tau_{\eta j}(X'\Xi_j Z_j)V(\hat{\delta}_j)(Z_j'\Xi_j X)$ where $V(\hat{\delta}_j)$ denotes the covariance matrix of $\hat{\delta}_j$.

Then the covariance matrix of the estimates of the labor supply function is given by

$$V(\hat{\theta}) = \sigma_\eta^2[X'X]^{-1}[X'(I - \tau_{\eta 1}^2\Xi_1 - \tau_{\eta 2}^2\Xi_2)X + Q_1 + Q_2][X'X]^{-1}.$$

Appendix B: Data

Dependent Variables

Criminal Income, Crime Participation Dummy:

In the 1980 interview, respondents were asked what fraction of their 1979 income was obtained by committing crime. There were six response categories: none, "a little", about one-fourth, about one-half, about three-fourths and almost all. To construct criminal income, I assigned each category a numerical fraction, then multiplied this fraction by total 1979 income. The numerical fractions I assigned were: 0, 0.1, 0.25, 0.50, 0.75, 0.9. Total income was computed as the sum of wages and salaries, business income, and transfer income. I also constructed a crime participation dummy equal to one if the respondent reported any income from crime, and zero otherwise.

Market Hours, Market Wages:

Market hours are hours worked on all jobs in 1979, taken from the 1980 interview data. Hourly wages were constructed by dividing 1979 wage and salary income by 1979 hours.

Explanatory Variables

Market Human Capital, Ability, Union Membership:

Years of education gives the highest grade completed as of May 1, 1979. The high school graduate dummy equals one if years of education exceed eleven. Potential experience is simply age in 1979- education -6. Ability is taken from the AFQT components of the ASVAB, which was administered in 1981. To eliminate race effects and the effects of education, I regressed the AFQT score on black and Hispanic dummies and individual dummies for years of education. The adjusted AFQT score used here is the residual from this regression. The union dummy equals one if the respondent's primary job at the 1980 interview was covered by collective bargaining.

Recent Arrests, Criminal Human Capital:

I constructed one dummy equal to one if the respondent reported being charged with or convicted of a crime during 1979, and another if he had been sentenced to probation during 1979. Similar measures were also constructed based on responses to questions about charges, convictions, and probation sentences prior to 1979. The brother variable is equal to one if any of the respondent's brothers were ever charged with, convicted of, or sentenced for a crime (from the 1980 survey), or if he was ever interviewed in jail between 1979 and 1991. The jail information was constructed from data about the respondent's brothers' places of residence at each interview.

References

Amemiya, Takeshi. "The Estimation of a Simultaneous Equation Generalized Probit Model." Econometrica 46, (September 1978): 1193-1205.

Becker, Gary S. "Crime and Punishment: An Economic Approach." Journal of Political Economy 76 (March/April 1968): 169-217.

Blumstein, Alfred, Cohen, Jacqueline, and Farrington, David P. "Criminal Career Research: Its Value for Criminology." Criminology 26 (February 1988): 1-36.

Blumstein, Alfred, Cohen, Jacqueline, Roth, Jeffrey A., and Vischer, Christy A. Criminal Careers and "Career Criminals". Washington, D.C.: National Academy Press, 1986.

Bound, John and Freeman, Richard B. "What Went Wrong? The Erosion of Relative Earnings and Employment Among Young Black Men in the 1980's. "Quarterly Journal of Economics 107 (February 1991): 201-232.

__________, and Johnson, George. "Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations." American Economic Review 82 (June 1992) 371-392.

Bureau of Labor Statistics. Handbook of Labor Statistics. Washington, D.C.: Government Printing Office, 1989.

__________. Handbook of Labor Statistics. Washington, D.C.: Government Printing Office, 1980.

Ehrlich, Isaac. "Participation in Illegitimate Activities: A Theoretical and Empirical Investigation." Journal of Political Economy 81 (1973): 521-565.

Elliott, Delbert S., and David Huizinga. "Reconciling Race and Class Differences in Self-reported and Official Estimates of Delinquency." American Sociological Review 45, (1980): 95-100.

Farrington, David P. "Age and Crime." In Crime and Justice: An Annual Review of Research, edited by Michael Tonry and Norval Morris. Chicago: University of Chicago Press, 1986.

Federal Bureau of Investigation. Crime in the United States: 1988. Washington, D.C.: General Printing Office, 1990.

__________, Age-Specific Arrest Rates and Race-Specific Arrest Rates for Selected Offenses, 1965-1988. Washington, DC: Government Printing Office, 1990.

__________, Crime in the United States: 1991. Washington, D.C.: General Printing Office, 1992.

Fishe, Raymond P.H., Trost, R.P., and Lurie, Phillip M. "Labor Force Earnings and College Choice of Young Women: An Examination of Selectivity Bias and Comparative Advantage." Economics of Education Review 1, (Spring 1981): 169-191.

Freeman, Richard B. "Crime and the Employment of Disadvantaged Youths." NBER Working Paper No. 3875, October 1991.

Gottfredson, Michael, and Hirschi, Travis. "The True Value of Lambda Would Appear to be Zero: An Essay on Career Criminals, Criminal Careers, Selective Incapacitation, Cohort Studies, and Related Topics." Criminology 24 (May 1986): 213-234.

Greenberg, David F. "Age, Crime, and Social Explanation." American Journal of Sociology 91 (July 1985): 1-21.

Greene, William H. Econometric Analysis. New York: Macmillan, 1993.

Grogger, Jeff. "Certainty vs. Severity of Punishment." Economic Inquiry 29 (April 1991): 297-309.

__________. "The Effect of Arrest on the Employment and Earnings of Young Men." Quarterly Journal of Economics 110 (February 1995): 51-72.

Gronau, Reuben. "Leisure, Home Production, and Work: The Theory of the Allocation of Time Revisited." Journal of Political Economy 85 (December 1977):1099-1123.

Heckman, James. "Shadow Prices, Market Wages, and Labor Supply." Econometrica 42 (July 1974):679-694.

__________ "Sample Selection Bias as Specification Error." Econometrica 47 (1979): 153-161.

__________ and MaCurdy, Thomas E. "New Methods for Estimating Labor Supply Functions: A Survey." Research in Labor Economics 4 (1981): 65-102.

Hindelang, Michael J., Hirschi, Travis, and Weis, Joseph G. Measuring Delinquency. Beverly Hills: Sage Publications, 1981.

Hirschi, Travis, and Gottfredson, Michael. "Age and the Explanation of Crime." American Journal of Sociology 89 (November 1983): 552-584.

Katz, Lawrence F., and Kevin M. Murphy. "Changes in Relative Wages, 1963-1987: Supply and Demand Factors." Quarterly Journal of Economics 107 (February 1992): 35-78.

Lemieux, Thomas, Fortin, Bernard, and Frechette, Pierre. "The Effect of Taxes on Labor Supply in the Underground Economy." American Economic Review 84, (March 1994): 231-254.

Maddala, G.S. Limited-Dependent and Qualitative Dependent Variables in Econometrics. Cambridge: Cambridge University Press, 1983.

Myers, Samuel B. "Estimating the Economic Model of Crime: Employment vs. Punishment Effects." Quarterly Journal of Economics 98 (February 1983): 157-166.

Newey, Whitney. "Generalized Method of Moments Specification Testing." Journal of Econometrics 29 (1985) 229-256.

Schmidt, Peter, and Ann D. Witte. An Economic Analysis of Crime and Justice: Theory, Methods, and Applications. Orlando, FL: Academic Press, 1984.

Singh, Inderjit, Squire, Lyn, and Strauss, John. "The Basic Model: Theory, Empirical Results, and Policy Conclusions." In Agricultural Household Models: Extensions, Applications, and Policy, edited by Inderjit Singh, Lyn Squire, and John Strauss. Baltimore: The Johns Hopkins University Press, 1986.

Sjoquist, David C. "Property Crime and Economic Behavior: Some Empirical Results." American Economic Review 63 (1973): 439-446.

Sullivan, Mercer L. Getting Paid: Youth Crime and Work in the Inner City, Ithaca, NY: Cornell University Press, 1989.

Tauchen, H., Witte, Anne D., and Griesinger, Harriet. "Deterrence, Work, and Crime: Revisiting the Issues with Birth Cohort Data." NBER Working Paper No. 2508, February 1988.

Tillman, Robert. "The Size of the 'Criminal Population': The Prevalence and Incidence of Adult Arrest." Criminology 25 (August 1987): 561-580.

Tittle, Charles R. Sanctions and Social Deviance. New York: Praeger, 1980.

Witte, Anne D. "Estimating the Economic Model of Crime with Individual Data." Quarterly Journal of Economics 94 (February 1980): 57-84.

Wolfgang, Marvin E., Figlio, Robert M., and Sellin, Thorsten. Delinquency in a Birth-Cohort. Chicago: University of Chicago Press, 1972.

Wolpin, Kenneth I. "A Time-Series Cross-Section Analysis of International Variation in Crime and Punishment." Review of Economics and Statistics 62 (August 1980): 417-423.

Table 1

Employment Status by Criminal Participation
(Column Proportions in Parentheses)

Employed in 1979?	Any Income from Crime in 1979? Yes	No	Total
Yes	259	816	1075
	(94.5)	(94.9)	(94.8)
No	15	44	59
	(5.5)	(5.1)	(5.2)
Total	274	860	1134
	(100.0)	(100.0)	(100.0)

Table 2
Participation Rates and Racial Participation Ratios for Various Measures of Property Crime

Variable	Participation Rate	Black/White Participation Ratio
Taken something from a store without paying?	0.25	1.13
Other than from a store, taken something not belonging to you worth less than $50?	0.22	0.75
Other than from a store, taken something not belonging to you worth more than $50?	0.09	1.00
Used force or strong arm methods to get money or things from a person?	0.07	1.87
Sold marijuana or hashish?	0.17	0.91
Sold hard drugs?	0.04	1.22
Tried to con someone?	0.21	1.25
Taken a vehicle for ride or drive without owner's permission?	0.10	1.55
Broken into a building or vehicle to steal something or just to look around?	0.09	0.77
Knowingly sold or held stolen goods?	0.17	1.17
Helped in a gambling operation?	0.04	0.95
Any property crime (i.e., answered yes to any of the above)?	0.54	1.03
Any income from crime?	0.24	1.52

Sample size: 1134

Table 3
Sample Means

Variable	Full sample	Non-criminals	Criminals
Log of market wage	1.318	1.343	1.238
	(0.699)	(0.687)	(0.729)
Market hours	1693.2	1754.8	1500.0
	(800.9)	(799.5)	(775.5)
Education	10.90	10.96	10.71
	(1.87)	(1.93)	(1.67)
High school graduate	0.549	0.583	0.445
Potential experience	3.66	3.68	3.59
	(2.00)	(2.04)	(1.84)
AFQT (adjusted)	-1.58	-1.51	-1.77
	(17.30)	(17.56)	(16.45)
Union member	0.265	0.256	0.296
Charged or convicted in 1979	0.100	0.077	0.172
On probation in 1979	0.022	0.019	0.033
Charged or convicted prior to 1979	0.152	0.123	0.241
On probation prior to 1979	0.060	0.044	0.109
Brother ever charged, convicted, on probation, or interviewed in jail	0.070	0.057	0.109
Non-labor income ($1,000's)	7.104	7.117	7.063
	(11.421)	(11.410)	(11.476)
Black	0.222	0.193	0.314
Hispanic	0.182	0.198	0.131
Urban	0.668	0.664	0.682
Married	0.155	0.174	0.095
AFQT missing	0.077	0.084	0.055
No brother in sample	0.717	0.721	0.704
Non-labor income missing	0.238	0.237	0.241
Sample size	1134	860	274

Note: Standard deviations in parentheses.

Table 4
Estimates of the Market Wage Equation

Variable	Coefficient
Education	0.102 (0.022)
High school graduate	0.187 (0.063)
Potential experience	0.082 (0.016)
AFQT (adjusted)	0.006 (0.001)
Union member	0.198 (0.045)
Charged or convicted in 1979	-0.150 (0.066)
On probation in 1979	-0.290 (0.138)
Black	-0.185 (0.054)
Hispanic	0.086 (0.057)
Urban	0.110 (0.043)
Married	0.139 (0.057)
λ (employment)	-0.139 (0.170)
Sample size	1075
R^2	0.174

Notes: Standard errors are in parentheses. In addition to the variables shown, the regression includes a dummy variable equal to one if the AFQT variable is missing. Missing AFQT scores were set to zero.

Table 5
GMM Estimates of the Structural Crime Probit

Variable	(1)	(2)	(3)	(4)
Log wage [mean derivative]	-0.631 (0.153) [-0.178]	-0.524 (0.150) [-0.148]	-0.526 (0.162) [-0.148]	-0.757 (0.175) [-0.214]
Charged or convicted before 1979	0.339 (0.121)	0.301 (0.115)	0.302 (0.125)	0.287 (0.119)
On probation before 1979	0.348 (0.177)	0.326 (0.167)	0.328 (0.182)	0.336 (0.172)
Brother ever charged, convicted on probation, or interviewed in jail	0.307 (0.171)	0.290 (0.161)	0.290 (0.175)	0.302 (0.166)
Black	0.200 (0.104)	0.224 (0.098)	0.225 (0.106)	0.165 (0.103)
Hispanic	-0.190 (0.120)	-0.209 (0.115)	-0.210 (0.122)	-0.201 (0.117)
Urban	0.113 (0.092)	0.093 (0.088)	0.095 (0.094)	0.124 (0.091)
Union member		0.355 (0.125)		0.290 (0.102)
Charged or convicted during 1979			0.356 (0.136)	0.320 (0.130)
Sample size	1134	1134	1134	1134
Over-identification test [d.f., significance]	24.69 [10, 0.006]	19.27 [9, 0.023]	16.82 [9, 0.052]	10.26 [8, 0.247]

Notes: Standard errors in parentheses. In addition to the variables shown, the regressions include a dummy variable equal to one if the respondent had no brother in the sample.

Table 6
Union/Non-Union Participation Ratios

Variable	Union/Non-union Participation Ratio
Taken something from a store without paying?	1.18
Other than from a store, taken something not belonging to you worth less than $50?	1.21
Other than from a store, taken something not belonging to you worth more than $50?	1.11
Used force or strong arm methods to get money or things from a person?	1.17
Sold marijuana or hashish?	1.14
Sold hard drugs?	1.52
Tried to con someone?	1.24
Taken a vehicle for ride or drive without owner's permission?	0.94
Broken into a building or vehicle to steal something or just to look around?	1.35
Knowingly sold or held stolen goods?	1.20
Helped in a gambling operation?	1.91
Any property crime (i.e., answered yes to any of the above)?	1.19
Any income from crime?	1.16

Sample size: 1134

Table 7
Additional GMM Estimates of the Structural Crime Probit

Variable	(1)	(2)	(3)	(4)
Log wage [mean derivative]	-0.668 (0.358) [-0.188]	-0.760 (0.174) [-0.214]	-0.875 (0.195) [-0.247]	-0.686 (0.175) [-0.193]
Education	0.043 (0.066)			
High school graduate	-0.241 (0.136)			
Potential experience	-0.021 (0.046)			
Non-labor income		0.001 (0.004)		
AFQT (adjusted)			0.003 (0.003)	
Married				-0.211 (0.133)
Charged or convicted during 1979	0.313 (0.147)	0.300 (0.130)	0.284 (0.128)	0.305 (0.133)
Sample size	1134	1134	1134	1134
Over-identification test [d.f., significance]	5.56 [5, 0.351]	9.81 [6, 0.132]	7.21 [6, 0.302]	10.26 [7, 0.384]

Notes: Standard errors in parentheses. In addition to the variables shown, all regressions include all variables from the specification in column (4) of Table 4. The model in column (2) also includes a missing value flag for non-labor income, which is equal to one if non-labor income is missing. The model in column (3) includes a similar missing value flag for the AFQT. In both cases, the missing values of the corresponding regressor are set equal to zero.

Table 8
Estimates of the Labor Supply Equation

Variable	(1)	(2)	(3)
Predicted log wage	612.3	731.7	713.5
	(127.4)	(99.7)	(113.5)
Non-labor income	-3.6	-3.3	-2.9
	(2.3)	(1.9)	(2.2)
Black	-165.6	-121.6	-198.5
	(75.6)	(58.1)	(69.8)
Hispanic	-92.1	-54.5	-57.2
	(69.0)	(57.1)	(63.3)
Urban	-154.2	-191.4	-173.5
	(57.8)	(78.2)	(55.4)
λ (employment)	105.3	58.0	171.9
	(327.8)	(290.0)	(346.4)
λ (crime)	431.2		
	(192.4)		
Sample size	816	1075	816
R^2	0.12	0.12	0.12
Over-identification test	11.17	4.59	9.59
[d.f., significance]	[10, 0.344]	[4, 0.332]	[4, 0.048]

Notes: Standard errors in parentheses. In addition to the variables shown, the regressions include a missing value flag for non-labor income which is equal to one if non-labor income is missing. Missing values of non-labor income were set equal to zero.

Table 9
Actual and Predicted Criminal Participation Rates, by Age

1. Actual participation rates

Age:	17-18	19	20	21	22-23
	0.375	0.259	0.282	0.218	0.189

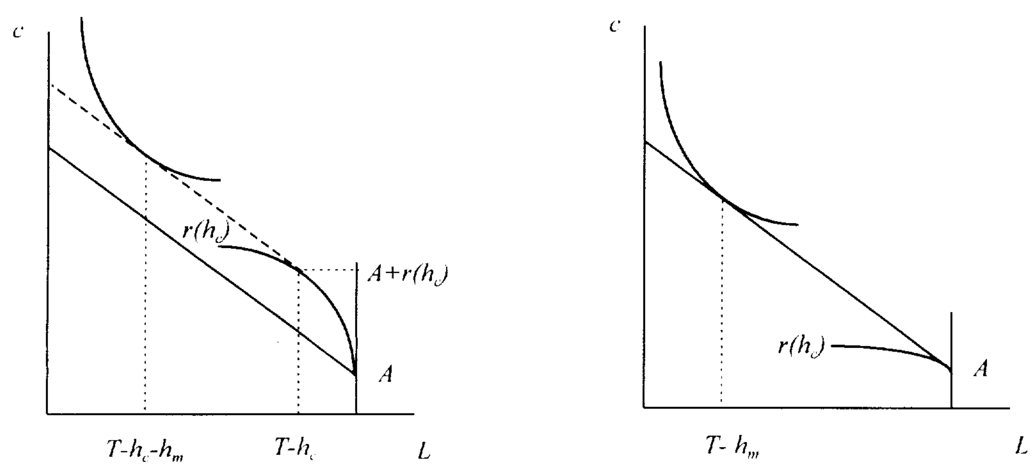
2. Predicted participation rates from models in Table 4

Age:	17-18	19	20	21	22-23
Column (1)	0.346	0.288	0.254	0.247	0.218
Column (2)	0.329	0.293	0.263	0.269	0.242
Column (3)	0.332	0.281	0.249	0.246	0.217
Column (4)	0.359	0.299	0.255	0.250	0.218

3. Predicted participation rates from models in Table 4 evaluated at mean wage

Age:	17-18	19	20	21	22-23
Column (1)	0.235	0.233	0.233	0.248	0.234
Column (2)	0.238	0.249	0.249	0.274	0.262
Column (3)	0.241	0.236	0.232	0.249	0.232
Column (4)	0.227	0.233	0.229	0.252	0.238

Figure 1



Consumer A

Consumer B