Table 5
Estimates of the Structural Crime Probit

<table>
<thead>
<tr>
<th>Variable</th>
<th>ML Probit (1)</th>
<th>GMM (2)</th>
<th>GMM (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log wage</td>
<td>-0.096</td>
<td>-0.633</td>
<td>-0.874</td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
<td>(0.175)</td>
<td>(0.211)</td>
</tr>
<tr>
<td></td>
<td>[-0.227]</td>
<td>[-0.179]</td>
<td>[-0.246]</td>
</tr>
<tr>
<td>Charged or convicted before 1979</td>
<td>0.339</td>
<td>0.247</td>
<td>0.318</td>
</tr>
<tr>
<td></td>
<td>(0.120)</td>
<td>(0.160)</td>
<td>(0.152)</td>
</tr>
<tr>
<td>On probation before 1979</td>
<td>0.402</td>
<td>0.351</td>
<td>0.357</td>
</tr>
<tr>
<td></td>
<td>(0.184)</td>
<td>(0.226)</td>
<td>(0.224)</td>
</tr>
<tr>
<td>Brother ever charged, convicted, on probation,</td>
<td>0.400</td>
<td>0.307</td>
<td>0.318</td>
</tr>
<tr>
<td>or interviewed in jail</td>
<td>(0.185)</td>
<td>(0.197)</td>
<td>(0.214)</td>
</tr>
<tr>
<td>Black</td>
<td>0.386</td>
<td>0.203</td>
<td>0.158</td>
</tr>
<tr>
<td></td>
<td>(0.105)</td>
<td>(0.119)</td>
<td>(0.132)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-0.111</td>
<td>-0.194</td>
<td>-0.191</td>
</tr>
<tr>
<td></td>
<td>(0.222)</td>
<td>(0.132)</td>
<td>(0.144)</td>
</tr>
<tr>
<td>Urban</td>
<td>0.563</td>
<td>0.115</td>
<td>0.145</td>
</tr>
<tr>
<td></td>
<td>(0.099)</td>
<td>(0.104)</td>
<td>(0.113)</td>
</tr>
<tr>
<td>Union member</td>
<td>...</td>
<td>...</td>
<td>0.325</td>
</tr>
<tr>
<td></td>
<td>...</td>
<td>...</td>
<td>(0.127)</td>
</tr>
<tr>
<td>(\sigma_{it})</td>
<td>...</td>
<td>0.410</td>
<td>0.411</td>
</tr>
<tr>
<td></td>
<td>...</td>
<td>(0.073)</td>
<td>(0.094)</td>
</tr>
<tr>
<td>Overidentification test'</td>
<td>...</td>
<td>19.03</td>
<td>9.89</td>
</tr>
<tr>
<td></td>
<td>...</td>
<td>(10.040)</td>
<td>(9.350)</td>
</tr>
<tr>
<td>(N)</td>
<td>1,073</td>
<td>1,134</td>
<td>1,134</td>
</tr>
</tbody>
</table>

Note: Standard errors are in parentheses. Mean derivatives are in square brackets. Degrees freedom and significance are in curly braces. In addition to the variables shown, the regressions include a dummy variable equal to one if the respondent had no brother in the sample. ML = Maximum likelihood, GMM = generalized method of moments.

were uncorrelated with the unobservable determinants of criminal productivity (\(\sigma_{it}\)).\(^{18}\) The coefficient on log wages in the first row is negative with a t-statistic of -1.57. Its magnitude indicates that, on average, a 10% increase in wages reduces the crime participation rate by .27 percentage points.

Generalized methods of moments estimates, which account for the endogeneity and partial observability of wages, are presented in column 2. The wage coefficient based on this estimator is substantially more negative than the ML probit coefficient, suggesting that the unobservable determinants of market productivity are positively correlated with the unobservable determinants of criminal productivity. The mean partial derivative of the probability of participating in crime with respect to the log wage is -1.179, indicating that a 10% increase in the wage would lead to a 1.8 percentage point reduction in the crime participation rate.

\(^{18}\) Only the 1,073 observations with nonmissing wage data are used in estimating this model.

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Market Wages and Youth Crime

Since the two estimators yield substantially different estimates of this key parameter, it is important to determine which of the estimators is better supported by the data. A one-degree-of-freedom Hausman test based on the log wage coefficients yields a t-value of -3.27, rejecting the null hypothesis that \( \mu_1 \) and \( \mu_2 \) are uncorrelated. A t-test of the method of moments estimate of \( \sigma_{12} \), shown near the bottom of the table, leads one to the same conclusion. Both of these tests indicate that the market wage is endogenous in the structural crime probit and, therefore, that the ML probit estimates are likely to be inconsistent.

Before discussing the remaining parameter estimates, it is worthwhile to reflect for a moment on the finding that \( \mu_1 \) and \( \mu_2 \) are positively correlated. What this says is that those determinants of wages that are orthogonal to education, experience, AFQT scores, and other variables in the wage equation are positively correlated with those determinants of criminal productivity that are orthogonal to the criminal human capital variables and the predicted wage variable in the structural crime probit. In other words, these unobservables are uncorrelated with education, test scores, and past crime, among other things, but nevertheless contribute positively to both market and criminal skill. Although it is beyond the scope of this article (as well as the data) to provide a detailed analysis of what these unobservables might represent, such characteristics as guile and tenacity come to mind.

Returning to the remaining coefficients in column 2, these estimates can be interpreted as showing how criminal human capital and other individual characteristics affect the consumer's criminal productivity 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

\[ P(C = 1) = P(X_2\beta_2 - X_1\beta_1 + \mu_2 - \mu_1 > 0) \]

\[ = P \left[ \frac{\mu_2 - \mu_1}{\psi} > \frac{- (X_2\beta_2 - X_1\beta_1)}{\psi} \right] \]

\[ (N1) \]

where \( \psi^2 = \sigma_1^2 + \sigma_2^2 - 2\sigma_{12} \). Since \( \sigma_1 \) and \( \beta_1 \) are estimated with the wage equation and \( \sigma_2 \) and \( \beta_2 \) are estimated by the structural crime probit, \( \psi \), and hence \( \sigma_{12} \), can be estimated from the coefficients in equation (N1). In principle, each coefficient provides a separate estimate; the estimates reported here are methods of moments estimates based on all the coefficients. The SEs were obtained by bootstrapping the sample.
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 last row of the table provides some evidence on the empirical adequacy of the exclusion restrictions that were suggested by the theory and that serve to identify the model. The overidentification test statistic is significant at the 5% level, rejecting the overidentifying restrictions. Some investigation revealed that the rejection resulted from excluding the union dummy from the model. The specification reported in column 3 includes the union dummy.

The coefficient on the union dummy is positive and significant, suggesting that, on average, union members are more likely to commit property crimes. Adding the union dummy to the model raises the wage coefficient somewhat but leaves the other coefficients essentially unchanged. This amended specification satisfies the overidentification test.

If this significant union effect reflects consumers' tastes, then it casts doubt on the validity of the exclusion restrictions suggested by the Gronau model. Alternatively, if it reflects differences in criminal productivity between union members and others, then it may reflect more on our limited state of knowledge regarding the determinants of criminal productivity than on any inadequacies of the theory. How might union membership raise one's productivity in crime? Union shops are larger than nonunion workplaces, on average, and union workers earn more than their nonunion counterparts. Both of these features of union establishments may facilitate such crimes as drug dealing and gambling racketeering.

Indeed, the data on specific crimes provide some support for this notion. 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 nonunion workers. The data show that, in general, union workers commit about 1.2 times as many property crimes as their nonunion counterparts. They are more heavily overrepresented in selling hard drugs and gambling, with participation ratios of 1.52 and 1.91, respectively. Thus it seems plausible that the significant union effect in the structural crime probit may reflect productivity differences rather than tastes.20

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

21 Groger (1997) provides more details on union as compared with nonunion participation rates.
Market Wages and Youth Crime

Table 6 presents estimates from alternative specifications that explicitly relax a number of the remaining overidentifying restrictions. These results provide additional information about the adequacy of the specification. First, they allow explicit tests of the hypothesis that variables related to tastes may be excluded from the crime participation probit. Second, these tests, which are based on Wald chi-square statistics for the additional regressors, may have greater power than the omnibus overidentification tests because they have fewer degrees of freedom. Finally, these results reveal an important piece of information not conveyed by the overidentification statistics: they permit the reader to assess how sensitive the key parameter—the log wage coefficient—is to relaxing the various exclusion restrictions.

In the first column of Table 6, 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. None of the coefficients are individually significant, however. The Wald chi-square statistic to test the joint significance of all three variables is 2.99, which fails to reject. Market human capital has no significant direct effect on criminal participation.

The next three columns introduce nonlabor income, the AFQT score, and marital status separately to the model. None are significant. The marriage variable, which of the set arguably best reflects tastes, has a $t$-statistic of only $-1.34$. Column 5 introduces the variables indicating sample-period involvement with the criminal justice system. The charged-or-convicted variable is positive and individually significant, but the probation dummy is negative, and the two variables are jointly insignificant, with a Wald statistic of 4.1. Column 6 introduces all variables except the market human capital variables, that is, all variables from columns 2–5. The joint Wald statistic is 6.52, with a significance level of .37.

The results in tables 5 and 6 suggest a number of general conclusions. First, with the possible exception of the union status variable, the exclusion restrictions suggested by the theory and used to identify the structural crime probit are supported by the overidentification tests. Since the union effect may have a productivity interpretation, the evidence seems largely consistent with the restriction that market and criminal productivity, rather than tastes, influence criminal participation.

Moreover, once the union effect is accounted for, the estimated effect of wages on crime participation is fairly insensitive to the inclusion of other variables in the model. The mean partial derivative of the probability

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22 In addition to the variables shown, all regressions include all variables present in col. 3 of table 5.
Table 6  
Additional GMM Estimates of the Structural Crime Probit

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log wage</td>
<td>-1.018</td>
<td>-0.577</td>
<td>-1.013</td>
<td>-0.799</td>
<td>-0.803</td>
<td>-0.868</td>
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<tr>
<td></td>
<td>(0.353)</td>
<td>(0.211)</td>
<td>(0.253)</td>
<td>(0.213)</td>
<td>(0.220)</td>
<td>(0.219)</td>
</tr>
<tr>
<td>Education</td>
<td>0.087</td>
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<td>...</td>
<td>...</td>
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<td>...</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>High school graduate</td>
<td>-0.305</td>
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<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td></td>
<td>(0.168)</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Potential experience</td>
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<td>...</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>...</td>
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<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Nonlabor income</td>
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<td>0.003</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>...</td>
<td>(0.003)</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>(0.001)</td>
</tr>
<tr>
<td>AFQT (adjusted)</td>
<td>...</td>
<td>...</td>
<td>0.004</td>
<td>...</td>
<td>...</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>...</td>
<td>...</td>
<td>(0.004)</td>
<td>...</td>
<td>...</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Married</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>-0.216</td>
<td>...</td>
<td>-0.198</td>
</tr>
<tr>
<td></td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>(0.157)</td>
<td>...</td>
<td>(0.163)</td>
</tr>
<tr>
<td>Charged or convicted during 1979</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>0.314</td>
<td>0.296</td>
</tr>
<tr>
<td></td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>(0.163)</td>
<td>(0.169)</td>
</tr>
<tr>
<td>Charged or convicted during 1979</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>-0.284</td>
<td>-0.342</td>
</tr>
<tr>
<td></td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>(0.342)</td>
<td>(0.353)</td>
</tr>
<tr>
<td>Charged or convicted before 1979</td>
<td>0.315</td>
<td>0.321</td>
<td>0.298</td>
<td>0.335</td>
<td>0.312</td>
<td>0.318</td>
</tr>
<tr>
<td></td>
<td>(0.156)</td>
<td>(0.153)</td>
<td>(0.164)</td>
<td>(0.149)</td>
<td>(0.152)</td>
<td>(0.156)</td>
</tr>
<tr>
<td></td>
<td>Coefficient</td>
<td>Standard Error</td>
<td>Coefficient</td>
<td>Standard Error</td>
<td>Coefficient</td>
<td>Standard Error</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-------------</td>
<td>----------------</td>
<td>-------------</td>
<td>----------------</td>
<td>-------------</td>
<td>----------------</td>
</tr>
<tr>
<td>or interviewed in jail</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>-.158</td>
<td>.151</td>
<td>-.185</td>
<td>.151</td>
<td>-.160</td>
<td>.145</td>
</tr>
<tr>
<td>Black</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>-.158</td>
<td>.151</td>
<td>-.141</td>
<td>.144</td>
<td>-.119</td>
<td>.114</td>
</tr>
<tr>
<td>Union member</td>
<td>.353</td>
<td>.142</td>
<td>.377</td>
<td>.127</td>
<td>.356</td>
<td>.125</td>
</tr>
<tr>
<td>u_2</td>
<td>.411</td>
<td>.077</td>
<td>.413</td>
<td>.075</td>
<td>.411</td>
<td>.049</td>
</tr>
</tbody>
</table>

**Note.** — *N = 1,134. GMM = generalized method of moments. AFQT = Armed Forces Qualifying Test. Standard errors are in parentheses. Mean derivatives are in square brackets. Degrees of freedom and significance are in squared brackets. In addition to the variables shown, the model in col. 3 includes a missing value flag for mother income, which is equal to one if neither income is missing, and the model in col. 5 includes a similar missing value flag for the AFQT. The model in col. 6 contains both flags. In all cases, the missing values of the corresponding regressor are set equal to zero. All models include a dummy variable equal to one if the respondent has no brothers in the sample.
Table 7
Estimates of the Labor Supply Equation

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted log wage</td>
<td>612.6</td>
<td>731.7</td>
<td>713.5</td>
</tr>
<tr>
<td></td>
<td>(127.6)</td>
<td>(99.7)</td>
<td>(113.8)</td>
</tr>
<tr>
<td>Nonlabor income</td>
<td>-2.6</td>
<td>-3.3</td>
<td>-2.9</td>
</tr>
<tr>
<td></td>
<td>(2.2)</td>
<td>(2.2)</td>
<td>(2.2)</td>
</tr>
<tr>
<td>Black</td>
<td>-165.6</td>
<td>-121.6</td>
<td>-198.8</td>
</tr>
<tr>
<td></td>
<td>(75.6)</td>
<td>(58.1)</td>
<td>(69.8)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-92.1</td>
<td>-34.9</td>
<td>-57.2</td>
</tr>
<tr>
<td></td>
<td>(69.6)</td>
<td>(57.1)</td>
<td>(53.3)</td>
</tr>
<tr>
<td>Urban</td>
<td>-134.2</td>
<td>-191.4</td>
<td>-173.5</td>
</tr>
<tr>
<td></td>
<td>(57.8)</td>
<td>(78.2)</td>
<td>(55.4)</td>
</tr>
<tr>
<td>λ (employment)</td>
<td>105.3</td>
<td>38.0</td>
<td>71.9</td>
</tr>
<tr>
<td></td>
<td>(327.8)</td>
<td>(290.2)</td>
<td>(346.4)</td>
</tr>
<tr>
<td>λ (crime)</td>
<td>431.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(192.4)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>816</td>
<td>1,075</td>
<td>816</td>
</tr>
<tr>
<td>(\delta)</td>
<td>.12</td>
<td>.12</td>
<td>.12</td>
</tr>
<tr>
<td>Overidentification test</td>
<td>11.17</td>
<td>4.59</td>
<td>9.59</td>
</tr>
<tr>
<td></td>
<td>[12, 346]</td>
<td>[4, 332]</td>
<td>[4, 648]</td>
</tr>
</tbody>
</table>

Note.—Standard errors are in parentheses. Degrees freedom and significance are in square brackets. In addition to the variables shown, the regressions include a missing value flag for nonlabor income that is equal to one if nonlabor income is missing. Missing values of nonlabor income were set equal to zero.

of participating in crime with respect to log wages ranges only from -.23 to -.29. Put differently, the wage elasticity of crime participation ranges from -.95 to -1.20. The value from the preferred specification, reported in column 3 of table 5, is -1.02. Youth participation in crime appears to be sensitive to labor market incentives.23

Finally, although the amended model passes all of the overidentification tests, it is of course impossible to say whether the just-identifying restrictions are satisfied. If not, the contrast between the ML probit and GMM estimates suggests that the GMM estimates may provide an upper bound of the true effect of wages on youth crime.

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 7. The effect of wages on market hours is large. On average, a 10% 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 1,693 hours

23 These estimates pertain only to the extensive margin of crime participation. With data on criminal hours, one could estimate the elasticity on the intensive margin, which also would be of interest.
per year, this implies an elasticity of .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 wage selection term is significant. The 
implication is that failing to account for youth crime may result in a 
mispecification 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 1,075 respondents who 
reported working in the previous year.

The wage coefficient from this naive model is 731.7. This is 25% larger 
than the estimate from column 1, which incorporates the information 
about crime. Although the difference across models is not significant, the 
point estimates suggest that 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 crimes 
but had no information about criminal human capital. Although the re-
searcher 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 would yield better 
estimates.

The results from this exercise are presented in the third column of table 
7. The wage coefficient is a bit smaller than the estimate in column 2, but 
the difference is slight. The wage parameter is still 16% too high. Failing 
to account properly for youth crime leads one to overestimate the elastic-
ity of youth labor supply with respect to the wage by a far 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 .408 
(.102). In contrast, the GMM estimates of the black coefficients in the 
structural crime probits in table 5 are no more than one-half that large.
To measure the contribution of wages, I performed a Oaxaca-type decomposition based on the specification in column 3 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 \( P(\ln w^b, X_2^b; \theta_j^b) \), where \( j = w, b \) denotes data and estimates from the white and black subsamples, respectively. The difference in crime participation rates between blacks and whites can be written as

\[
P(\ln w^w, X_2^w; \theta_j^w) - P(\ln w^b, X_2^b; \theta_j^b)
\]

\[
= [P(\ln w^w, X_2^w; \theta_j^w) - P(\ln w^b, X_2^b; \theta_j^b)]
\]

\[
+ [P(\ln w^b, X_2^b; \theta_j^w) - P(\ln w^b, X_2^b; \theta_j^b)].
\]

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 differences in the race-specific regression coefficients. This step of the exercise showed that 6.0 percentage points of the 13.7 percentage point 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 (\( \Delta \)) to the wage of each black in the sample. The resulting quantity, \( P(\ln w^w, X_2^w; \theta_j^w) - P(\ln w^b + \Delta, X_2^b; \theta_j^b) \), accounted for all but 2.4 percentage points of the racial differential in crime rates. In other words, the black-white wage gap explains 3.6 percentage points, or 26%, 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-1970s, real wages paid to men 16–24 years old who work full time have fallen 20.3% (Bureau of Labor Statistics 1982, 1989). Real hourly wages

\[24\] Algebraically,

\[
P(\ln w^l, X_2^l; \theta_j^l) = \frac{1}{n_j} \sum_n \Phi \left[ X_n^l (\frac{\beta_j}{\sigma_j})' - \left( \frac{1}{\sigma_j} \right)' \ln w^l \right],
\]

where the \( i \) subscript explicitly denotes individual observations and \( n_j \) is the number of observations in group \( j \).
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paid to male hourly workers between 16 and 24 years old, which may provide a better gauge of the labor market opportunities facing young, relatively unskilled men, behaved similarly, falling by 23.0%.

In response to a 20% fall in wages, the model predicts that youth participation in crime should rise by 20%. Unfortunately, data on criminal participation do not exist. The Federal Bureau of Investigation (1990b) does publish age-specific arrest rates, however, that may provide at least a rough gauge of trends in participation rates. Between the early 1970s and the late 1980s, arrest rates for 16-to-24-year-old males rose from 44.6 to 52.6 per 1,000 population, a gain of 18%.

This calculation is not made to suggest that falling wages literally explain the entire rise in youth arrests. Other factors drove changes in behavior over this time period as well, as evidenced by increases in arrests among adults, who generally experienced smaller declines in real wages. Rather, this calculation is offered to indicate that wage trends may have played an important, though not necessarily exclusive, role in increasing youth crime.

The model also predicts that youth labor supply should fall by 7.4% in response to a 20% 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%. For comparable 20- to 24-year-olds, market labor supply fell 3%. The weighted average decrease was 15%.

Thus, for both youth crime and labor supply, the predictions from the model are consistent with 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 rise in youth crime during the 1970s and 1980s.

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 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 (1983) 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 have asked whether wages might explain the shape of the age-crime profile. For economists, this is the natural hypothesis to consider. Wages measure the opportunity cost of crime and grow with age as a worker accumulates labor market experience.

Table 8 presents the evidence. The first row 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 twenties.

The next row presents predicted participation rates from the specification of the structural crime probit reported in column 3 of table 5. The predictions largely follow the pattern of the actual data. Considering that neither age nor labor market experience were included in the structural crime probits, the model does a reasonably good job at replicating the age distribution of crime.

Do wages explain the pattern? The last row reports the mean predicted participation rates by age that result when wages are fixed at the sample average. 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.25

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

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25 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.
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define and measure crime make such comparisons problematic. Farring-
ton (1986) attempted such a comparison between England and the United
States and concluded that their age-crime relationships were similar. Be-
cause there were differences in crime categories (all crimes in England
vs. nonviolent crimes in the United States) and crime measures (arrests
in the United States vs. convictions and cautions in England) across the
two countries, however, it is not clear that one can draw any firm conclu-
sions 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 phenom-
enon. Blacks typically earn less than whites, and this wage gap explains
about one-fourth 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 during the 1970s and 1980s. 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 patterns than has been
recognized previously. Nevertheless, it would be desirable to further dem-
strate their robustness. Although the estimates presented here are
largely insensitive to changes in the econometric specification, that spec-
fications 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 a subscript $i$ to denote individual observa-
tions. The corresponding expressions without $i$ subscripts now refer to the
data matrix whose typical row is the $i$th observation.

Rewrite equation (8) more compactly as

$$
\hat{h}_{ni} = s_i \beta + \gamma_i \lambda_{ni} + \nu_i \lambda_{ni} + \psi_{ni}.
$$

(8')
where \( S_i = [X_{i1}, \ln \omega_i, A_i] \), \( \beta = [\beta_1, \beta_2, \beta_3]' \), \( \gamma = \sigma_{\eta \ln \omega} \), and \( \lambda_i = \lambda_i(\omega_i) \). It will suffice to define \( S_i \) in terms of \( \ln \omega_i \) because all of the other regressors in equation (8') are included in the expression for \( \ln \omega_i \). In other words, the predicted values for \( \ln \omega_i \) account for the sample selection corrections, as noted in footnote 9. It will be convenient to write equation (8') even more compactly as

\[
\gamma = X_\gamma \theta + \nu_2, \tag{8''}
\]

where \( X_\gamma = [S_i, \lambda_i, \lambda_{ii}] \) and \( \theta = [\beta', \gamma', \lambda_i]' \).

The error term \( \nu_2 \) is heteroskedastic, with variance \( \text{var}(\nu_2) = \sigma_\nu^2(1 - \tau_{1i}^2 \xi_{ii} - \tau_{2i}^2 \xi_{ii}) \), where \( \sigma_\nu^2 = \text{var}(\nu_1) \) and \( \xi_{ii} = \lambda_i(\lambda_i - Z_i \delta_i) \). Define \( \Xi_i \) to be the diagonal matrix with the terms \( \xi_{ii} \) on the diagonal, and \( Q_i = \tau_{2i}(X'\Xi_i X) V(\delta_i)(Z_i \xi_i X)^{-1} \), where \( V(\delta_i) \) denotes the covariance matrix of \( \delta_i \). Then the covariance matrix of the estimates of the labor supply function is given by

\[
V(\hat{\theta}) = \sigma_\nu^2 (X'X)^{-1}[X' (I - \tau_{1i}^2 \Xi_{1} - \tau_{2i}^2 \Xi_{2}) X + Q_1 + Q_2] (X'X)^{-1}.
\]

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, .1, .25, .50, .75, and .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 number of hours in 1979.

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 exceeded 11. Potential experience is simply age in 1979 – education – 6. Ability
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...is taken from the AFQT components of the Armed Services Vocational Aptitude Battery 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’ (or brothers’) places of residence at each interview.

References


LePreux, Thomas; Portin, Bernard; and Frechette, Pierre. “The Effect of
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