Abstract

Following Jeffrey Grogger's 1998 analysis, I utilize a time allocation model to study the responsiveness of youth crime to market wage rates. The decision to commit crime will be considered a labor market phenomenon, influenced by the financial returns it offers in comparison to legal work alternatives. To test the theoretical implications of the model, I use data gathered from the National Longitudinal Survey of Youth. Moreover, I expand on Grogger's model by increasing the sample size and utilizing different measures of criminal involvement and non-wage income. My estimates support Grogger's findings such that the crime choice is motivated by market wages.

Understanding the crime choice –

The role market wages.

Kathleen E. Wirth

University of North Carolina at Chapel Hill

Chapel Hill, North Carolina

July 7, 2003

***Kathleen Wirth graduated from the University of North Carolina at Chapel Hill in May 2003 with a B.A. in economics. She is currently working at RTI International in Research Triangle Park, NC as an Economist.**

Acknowledgements

A million thanks to my advisor, David Blau, for all of his guidance and patience throughout this process. I could not have asked for a better advisor.

To the Statistical Consulting staff at the Odum Institute for all of their technical advice on this project.

To the house with the pink doors - Karey, Christie, Vaishali, Sofia and Kim - thank you for supporting me. I feel lucky to have met such amazing women.

To Nathan for letting me sequester his computer and statistics books for weeks and teaching me to think in terms of variables, not ideas. Thank you for believing in me.

Contents

(i.) List of Figures and Tables

Figures

Tables

Section 1: Introduction

Crime and crime prevention constitute significant economic activities in the United States with huge social implications for both criminals and law-abiding citizens. In 1997 authorities reported nearly 13.5 million crimes, while citizens reported being victimized almost three times as often. In the same year, the budget for the criminal justice system constituted more than 100 billion dollars. Criminal offenders tend to be young – in 1995 72 percent of those arrested fell between 17 and 34 years old (Freeman 1999). The economics of crime is interesting because crime is closely linked to poverty and a lack of education and it is concentrated within distinct populations, specifically young men. For example, 15.9 percent of young men reported selling marijuana at least once in 1980 (Freeman 1999). These crime participants typically lack formal education and labor market skills, have trouble maintaining employment, and consequently receive low wage offers in legitimate labor markets.

Given these conditions, some young people may view criminal activities as an attractive alternative to legitimate labor market opportunities. These youth may consider all available economic opportunities, both legal and illegal, in the labor market. In a sense, they are entrepreneurs, choosing the combination of criminal and legitimate activities that produces the highest expected utility, accounting for the possibility of arrest and incarceration and the social stigma associated with crime. Furthermore, the risky nature of crime implies that participants are likely to display lower levels of risk-aversion than workers in legitimate labor markets.

The main issue addressed in this paper is the responsiveness of youth crime to labor market incentives. To what extent do market wage offers in legitimate jobs affect an individual's decision to commit crime? If criminal behavior responds to wage rates, then the decision to commit crime could be considered a labor market phenomenon, with crime being a form of self-employment. An economic perspective suggests that the decision to commit crime will be influenced by the financial returns it offers in comparison to legal work alternatives. Economic theory also predicts that the probability of criminal sanctions (arrest, conviction and incarceration) will affect the crime participation decision. I suggest that individuals with low wage offers in legitimate jobs will be more likely to commit crime for given financial returns to criminal activities.

Section 2: Literature Review

Much of the empirical research conducted on the economics of crime has utilized data from the National Longitudinal Survey of Youth (U.S. Department of Labor, Bureau of Labor Statistics).

Grogger (1998) utilizes the data gathered from the 1980 crime section of the NLSY in a time allocation model of crime participation. In the model, consumers maximize their utility by choosing a combination of legitimate and illegal work subject to their expected returns to wages and crime. It is assumed that an individual will choose to work if the market wage offer exceeds the reservation wage. An individual will choose to commit crime if the returns to crime for the first hour of activity exceed the reservation wage. There are two primary implications of this assumption. First, consumers choose how much time to spend participating in criminal activities and then how much time to spend working in the legitimate labor market. Second, the consumer optimizes his utility through legal wage offers and criminal returns – tastes do not factor into the crime choice.

In specifying the sample, women, men enrolled in school, men enlisted in the military and those respondents interviewed in jail in 1979 or 1980 are excluded from the sample. This is done under the assumption that men commit the overwhelming majority of crimes and the desire to limit the sample to only those individuals whose alternatives to leisure would be work or crime. Specifically, 1,075 out of the restricted sample of 1,134 young men reported being employed in 1979 (94.8 percent). Additionally, sample means indicate that criminals earn about 11 percent less and work about 6 fewer full-time work weeks than non-criminals in the legitimate labor market. These initial findings are consistent with the theoretical assumption that criminals freely substitute income-generating criminal activities for legal market work.

Grogger finds that 24 percent of his sample reported earning income from illegal activities, while 54 percent admitted to committing at least one crime that could have generated income for the individual. This finding is attributed to poor data quality – several of the activity-specific questions in the crime module could include activities that are not crimes. For example, taking someone's car without permission may be an indicator of motor vehicle theft like breaking into a building can be a prelude to burglary. But, it could also mean taking one's parent's car without permission or sneaking into an abandoned building. Additionally, even if an individual reports participation in property crimes or income generating activities, not every crime yields financial rewards. For instance, an individual might have helped in a gambling operation, but participation does not necessarily imply payoffs. Similarly, holding stolen goods may not involve financial benefits to the individual. Given the broad nature of the questions, a criminal income measure is used rather than activity-specific participation in the empirical analysis. The advantage of the income-based variable is that it indicates that the individual reaped financial rewards for at least one crime.

The study also finds the illegal income measure more reliable than the individual crime participation measures because of possible underreporting by survey respondents. Overall property crime participation for young black men is relatively equal to their white counterparts. Yet this finding contradicts actual police arrest records, which reveal a substantially higher rate of crime participation for blacks as opposed to whites. Likewise the ratio of participation for the illegal income measure is much higher. Grogger asserts that low participation rates for blacks invalidate the activity specific measures, and consequently, estimates based on the specific data yield results that disagree with economic theory – namely that higher wages translate to increased crime participation.

Employing a structural crime probit model with the income-based measure as the dependent variable and accounting for the endogeneity of market wages, the study predicts a 10 percent increase in wage in legitimate employment reduces crime participation by 1.8 percent. This assumption of endogeneity implies that the unobservable determinants of legitimate market productivity are positively correlated with the unobservable determinants of criminal productivity. Assuming instead that the wage rate is exogenous produces estimates that predict a 10 percent increase in market wages reduces crime participation by .27 percent. In the table of results below, column 1 (the Maximum Likelihood Probit model) represents estimators that do not allow for correlation, while column 2 (GMM – Generalized Methods of Moments model) displays estimators which account for correlation between criminal and market productivity through the endogeneity of wages.

Table 5
Estimates of the Structural Crime Probit

Variable	Estimator: ML Probit (1)	GMM (2)	GMM (3)
log wage	−.096	−.633	−.874
	(.061)	(.175)	(.211)
	[−.027]	[−.179]	[−.246]
Charged or convicted before 1979	.339	.341	.318
	(.128)	(.140)	(.152)
On probation before 1979	.400	.351	.357
	(.184)	(.206)	(.224)
Brother ever charged, convicted, on probation, or interviewed in jail	.400	.307	.318
	(.185)	(.197)	(.214)
Black	.386	.203	.138
	(.105)	(.119)	(.132)
Hispanic	−.111	−.194	−.191
	(.122)	(.135)	(.144)
Urban	.063	.115	.145
	(.093)	(.104)	(.113)
Union member	...	...	.325
			(.127)
σ_{12}	...	.410	.411
		(.075)	(.054)
Overidentification test	...	19.03	9.89
		{10, .040}	{9, .360}
N	1,075	1,134	1,134

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.

The table of findings also shows estimates of how criminal human capital and other individual characteristics affect an individual's choice to commit crime. The number of times an individual was charged or convicted of a crime before 1979 and whether or not the individual had a brother who had been previously charged, convicted or incarcerated provide a proxy for criminal human capital. The coefficients for these measures are positive and significant suggesting that criminals learn by doing – Grogger postulates that as an individual commits more crime, his criminal productivity increases, pushing him to commit more crime.

In the study, a market wage equation is estimated to test the hypothesis that crime participation in the sample period negatively affects legitimate market wages. Being charged or convicted of a crime in 1979 reduced an individual's wage rate by 15 percent. Furthermore, being on probation in 1979 reduced wages on average by 29 percent. Grogger hypothesizes that this reduction in wages may stem from the contractual requirements of probation, rather than criminal participation. Employment is often a stipulation of an ex-prisoner's probation and consequently, individuals may take jobs at lower market wages. Under this contention, it is asserted that low wage rates may not result from lower market productivity, but as a means to insure freedom. Further tests indicate that the criminal productivity proxies in the structural crime probit model are statistically insignificant and fail to fully explain the individual's low wage rate. This may indicate that crime participation has only a marginal or short-term negative effect on a criminal's earnings in legitimate employment.

Like Grogger, Fairlie (2002) also employs information gathered in the NLSY's 1980 crime module. But, this study uses the data to estimate the magnitude of the effects of individual preferences, basic skills and ability on probability of choosing self-employment work. Specifically, the relationship between drug dealing as a youth and legitimate self-employment in later years is examined to provide indirect evidence of preferences of self-employed individuals assumed in the theoretical model – namely preferences toward risk, autonomy and entrepreneurial ability.

In the model, drug dealing – frequency and level of participation – is used to proxy these preferences because the nature of drug dealing makes it more attractive to individuals with these preferences. Fairlie points to ethnographic studies of drug dealers in San Francisco which indicate that drug dealing is an inherently risky activity – dealers face substantial potential losses in profits from having their merchandise confiscated by the police, stolen by other competing dealers or addicted, irrational consumers (Fields 1986). Thus, individuals with low levels of risk aversion may be more likely to participate in drug dealing, holding everything else equal. The same study found that profitable drug dealers posses a higher level of entrepreneurial ability. Interviews with individual drug dealers show that these individuals strategically sell at different locations and at different times during the day to maximize profits and minimize the probability of arrest or competition from other dealers.

In the Fairlie study, drug dealing is defined as selling marijuana and/or hard drugs more than six times during 1980. Using stricter definitions of drug dealing (selling more than 11 times and selling more than 51 times) produces larger coefficients that remain statistically significant on the probability of self-employment. This finding is consistent with the hypothesis that individuals who sell drugs on a more regular basis possess higher levels of entrepreneurial abilities than others who sell less frequently.

Furthermore, the study finds that self-employed individuals possess high levels of human capital that are not rewarded to the same extent in wage or salary work. Specifically, individuals who participate in drug dealing as a youth are 11 to 21 percent more likely to engage in self-employment as an adult. Basic skills and ability – measured by years of education and AFQT scores – which have large effects on an individual's wage rate in the legitimate labor market, have smaller effects on the probability of choosing self-employment. Youth who sell drugs more frequently or report higher levels of illegal income also have higher probabilities of choosing self-employment later on than other youth drug dealers.

While the economic model of crime predicts that market wage offers in legitimate jobs will impact an individual's decision to commit crime, it also implies that criminal sanctions will have a negative influence as well. Empirical research has not yielded robust results specifying the degree to which legitimate wages affects the crime decision. Some previous studies have concluded that raising legal wage offers has little effect on preventing crime, while increases in the certainty and severity of criminal sanctions significantly impact the crime choice. Likewise, significant drops in the number of police normally observed during police strikes are correlated with increases in crime. Crime rates have been known to increase during riots, where the probability of being caught decreases (Freeman 1998). But evidence supporting this contention is relatively weak when investigating using individual data. For example, Witte (1980) analyzed the post-release activities of men in the North Carolina prison system. The study found marginal support for the hypothesis that an increased probability of criminal sanctions negatively affects the criminal participation of ex-prisoners and even less evidence as to the impact of legitimate market opportunities.

But other studies have produced contrary conclusions, pointing to the improvement of legitimate labor opportunities as a dominant deterrent to crime for the individual. Myers (1983) concluded that the effects of improved legitimate employment opportunities largely reduced recidivism rates in the 12 months after release from prison. Using data from 432 men released between 1971 and 1972 from Maryland's prison system, Myers found that in every month after the first month, higher weekly wage earnings increased the probability that an individual would not be rearrested. For example, conditional on not being rearrested during the first month, increasing an individual's wage rate by 10 percent increases the odds in favor of making it through the second month without re-arrest by .01. In the same study, evidence to the certainty and severity of criminal sanctions are weak for each month. Certainty of criminal sanctions was obtained using the ratio of previous convictions to previous arrests and severity was measured by the length of term previously served by the individual for the most recent offense. The coefficients on the certainty and severity of criminal sanctions in nearly every post-release month are statistically insignificant.

Section 3: Theoretical Framework

I use a time allocation model to analyze the individual's decision on how much crime to commit and how much to work in the legitimate labor market as a function of the returns to crime and the wage rate. Self-employed individuals typically possess a number of unobservable characteristics not normally rewarded to the same degree in wage or salary work as in self-employment. These qualities – low levels of risk-aversion, preferences for independence in work and increased entrepreneurial capabilities – make a model of self-employment a logical approach for understanding the impact of wages on participation in crime.

Criminal activities will be defined as a form of self-employment in which, in contrast to legitimate labor market alternatives, the wage rate is not fixed and not taken as given by the worker. Instead, the individual faces declining marginal returns to criminal labor. This could result from two distinct causes: (1) the more hours a person spends engaging in criminal activities, the higher the probability of arrest or incarceration, and (2) the easiest activities will be taken first; more hours devoted to crime will yield lower marginal returns because of the greater effort required to successfully carry out more difficult crimes.

In the model, criminal activities are treated as the output of a small business. Only two inputs are utilized in the production process – time and capital goods. For example, an individual, acting as a firm and choosing to commit a robbery, will target a house with unlocked doors before choosing a house equipped with an alarm system. In the first robbery, given quantities of inputs (time and break-in tools) are used in the production process. In the second robbery, the individual may have to commit more time to the second house in order to disarm the security system and thereby increasing the firm's cost of production. The criminal may also need to incorporate more advanced capital goods to break into the second house as opposed to simply breaking a window at the unarmed house or entering when the owner is not at home. Similarly, in producing a successful robbery, the probability of getting caught at the first house is presumed to be lower relative to the second house, thus increasing the expected returns to breaking into the first house.

It also will be assumed that leisure has been pre-determined by the individual. The decision is how to allocate non-leisure time between crime and legitimate employment. Finally, I will assume that work hours can be freely allocated between crime and legitimate employment. An individual can choose a corner solution such as devoting all work hours to crime or legitimate employment or an interior solution with some work hours allocated to crime and some to legitimate employment. However, I also assume that any given work hour is devoted exclusively to crime or legitimate employment: no crime is committed while on the job at a legitimate employment.

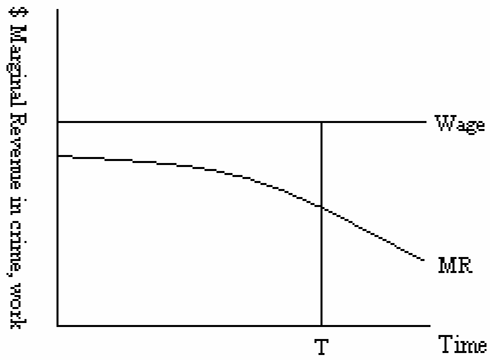

Figure 1

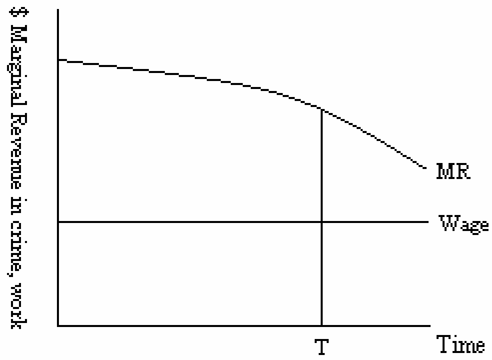

Figure 2

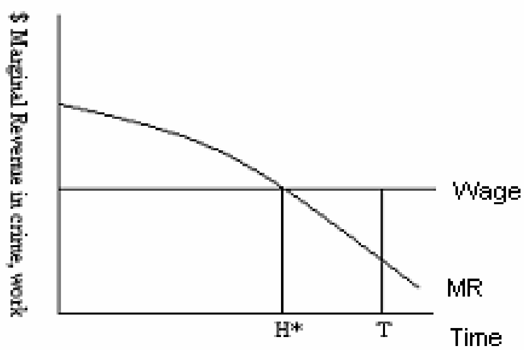

Figure 3

In Figure 1 the individual's wage in legitimate employment is always greater than the expected marginal returns to crime, even in the first hour of criminal activity where the marginal return is the highest. Thus the individual chooses a corner solution in which all work hours are allocated to legitimate employment. In Figure 2, the individual's wage in legitimate work is always lower than the expected marginal returns to crime, up to the last hour of allocated to work. As in Figure 1, a corner solution is chosen, but in this case all work hours are devoted to criminal activities. Figure 3 demonstrates the case of an individual who chooses an interior solution where the expected marginal returns to crime equals the wage rate. For every work hour up to H*, the individual will choose crime over legitimate employment. But the individual will also allocate T – H* hours to legal work, where the wage rate exceeds the expected marginal return associated with crime.

The decision to commit crime depends on the expected benefits and costs, with benefits being obtaining financial rewards and costs being imprisonment, fines, possible physical risks including injury or death incurred on the job and the social stigma associated with criminal activities (incarceration or possessing an arrest record may signal to future employers dishonesty or ineptitude). These factors together determine the shape and location of the expected marginal return to crime curve. Labor market incentives act to influence workers on the cost-side – the model predicts, in accordance with my hypothesis, that workers with high-paying opportunities in legitimate employment will commit less crime than workers with low-paying jobs because individuals with higher wage offers face a greater opportunity cost from crime. Their time spent in legitimate labor markets is more valuable and, in committing crime, they have more income to lose than lower paid workers from arrest and incarceration.

Section 4: Data and Estimation

The data are taken from the NLSY, which comprises a nationally representative, cross-sectional sample of 12,686 young people living in the United States and ages 14-21 as of December 31, 1979.

There are three distinct sub-samples within the NLSY designed to analyze the labor market experiences of populations such as women, blacks, Hispanics and economically disadvantaged individuals. The first sub-sample includes a cross-sectional representation of 6,111 non-institutionalized civilian young people. Almost all of the respondents in this sub-sample were eligible for participation during each subsequent survey year. The second sub-sample includes 5,295 respondents designed to over-sample Hispanics, blacks and economically disadvantaged non-Hispanic and non-black young people. The third sub-sample includes 1,280 individuals enlisted in one of the four branches of military service as of September 1, 1978. The supplemental low-income white sample was discontinued in 1990 and the military over sample in 1984. The cohort was interviewed annually from 1979 to 1994 and biannually thereafter.

Table 1
Summary of NLSY79 Data

	Cross-Sectional Sample		*Supplemental Sample*		*Military Sample*	
	Percentage	*N*	*Percentage*	*N*	*Percentage*	*N*
Men		3003		2576		824
Non-black, Non-Hispanic	81.2	2439	28.8	742 (poor)	73.9	609
Black	11.5	346	42.9	1105	19.6	162
Hispanic	7.3	218	28.3	729	6.4	53
Women		3108		2719		456
Non-black Non-Hispanic	79.7	2477	33.1	901 (poor)	75.0	342
Black	13.0	405	39.2	1067	19.5	89
Hispanic	7.3	226	27.6	751	5.5	25

Within the supplemental sample "(poor)" denotes economically disadvantaged non-black and non-Hispanic respondents. (Source: US Department of Labor, Bureau of Labor Statistics. www.bls.gov/nls/79guide)

In 1980, the NLSY included a crime module with questions on participation in and income from illegal activities, including selling hard drugs, shoplifting, and auto theft in 1979. In total the survey contained questions on participation for 10 different property crimes. The module also included questions related to the respondents' arrest and court proceedings in 1979 and information on income from criminal activities. Respondents were asked to estimate the percentage of their total income that came from illegal activities – possible answers included none, very little, about one-fourth, one-half, three-fourths and almost all. Unfortunately, longitudinal information on crime participation is not available from the NLSY because the crime section was not administered again after 1980.

To test the theoretical implications of my model, I use the information gathered in the 1980 crime module of the NLSY to estimate two crime participation probit models – the first using a general participation dummy dependent variable and the second using activity-specific dependent variables. Both model specifications are estimated with a restricted and full sample, using both predicted wage and actual wages. The restricted sample follows Grogger's 1998 analysis and only includes male respondents not enrolled in school or the armed forces in 1979. Only individuals whose primary substitute for leisure is work or crime will be considered in the restricted sample model specification. I have estimated both models using the full sample, with different measures of the wage rate and with different crime participation dependent variables to replicate and examine the robustness of Grogger's results.

In the first model I use the criminal income measure of crime participation as the dependent variable. In the model, the dependent variable equals 1 if the respondent reported earning any income from illegal activities and 0 otherwise. The advantage of this model is that the respondent successfully earned income from crime participation in at least one activity – a fact that cannot be assumed using activity specific crime participation data. Even if an individual reports engaging in income-generating criminal activities, it is not always clear from the data that income was actually earned as a result.

In the second model, dummy participation variables for crimes that could be considered income-generating activities (or property crimes) are utilized as the dependent variables. Each dependent variable in the model – shoplifting, stealing something worth less than $50, stealing something worth more than $50, robbery, selling marijuana, selling hard drugs, gambling – equals one if the respondent committed the crime at least one time and zero if the respondent did not commit the crime at all.

To proxy criminal experience in both models, a dummy variable equaling one if the respondent had been charged with a crime before 1979 is included. I expect the coefficients for this measure to be positive because criminals learn by doing – as an individual commits more crime, his criminal productivity increases, pushing him to commit more crime. A dummy variable for urban location is also included under the reasoning that an urban location may increase an individual's criminal productivity because there are more potential targets in cities as opposed to rural or suburban areas.

To account for the endogeneity of market wages, I estimate a separate log wage equation to generate a predicted wage for each respondent. Only 43 percent of individuals interviewed in 1980 reported a wage rate for their current or most recent job. But not working only implies an unobserved wage rate. For the purposes of the model, I assume that every individual, even if they decide not to work in a given year, has a wage rate (based on a set of characteristics including age, race, gender, ability and location of residence that I assume are exogenous) that they would have received in a legitimate labor market. The log wage equation used to generate a predicted wage for the entire sample is reported below. The Armed Forces Qualifying Test score, adjusted for age, is included as a measure of ability. The adjusted measure was constructed through individual age dummies that were used to predict an AFQT score for the entire sample. Education (highest grade completed at the 1980 interview) is an endogenous variable because it is a choice variable not pre-determined outside of the model. Therefore, oldest sibling, mother and father's education will be used as explanatory variables in the wage equation.

$$(1) \qquad Log\ wage\ rate_i = \alpha + \beta_1(age_i) + \beta_2(black_i) + \beta_3(Hispanic_i) + \beta_4(urban_i) + \beta_5(gender_i) + \beta_6(AFQT_i) + \beta_7(edu\_mom_i) + \beta_8(edu\_dad_i) + \beta_9(edu\_sibl_i) + \varepsilon_i$$

Tests on interactions between AFQT, urban and gender yielded a F-statistic of 1.29, failing to reject the null hypothesis that all of the coefficients on the interaction terms are zero.

The results of the reduced form log wage equation are presented below in Table 2. The coefficients were then used to generate a predicted wage rate for the entire sample. The signs on the coefficients are surprising – for example, AFQT scores are negatively correlated with wages or increases in an individual's score would decrease wages in a legitimate work. This could be attributed to the fact that individuals with higher AFQT scores may be more likely to be enrolled in school or have part-time jobs with low wages. Also, the coefficients on mother and oldest sibling's education are positive while the coefficient on father's education is negative, but very small.

Table 2
Estimates of the Reduced Form Log Wage Equation

Variable	***Coefficient***	
*Age at 1980 interview***	.082	(.004)
Black	-.014	(.015)
*Hispanic**	.033	(.018)
*Urban location***	.092	(.014)
*Gender=Male***	.182	(.011)
*AFQT score***	-.013	(.006)
Education – Mother	.002	(.002)
Education – Father	-.0004	(.002)
Education – Oldest Sibling	.0005	(.0007)
N	4358	
Adjusted R^2	.2061	

Note: Standard errors are in parentheses.
AFQT=Armed Forces Qualifying Test
***=significant at 5 percent level of confidence.*
**=significant at 10 percent level of confidence.*

Summary statistics are presented below in Table 3. The actual wage rate represents the hourly rate of pay in dollars at the respondent's current or most recent job when interviewed in 1980. Only those reported wage rates greater than or equal to $1 were included in the calculations.

Table 3
Wage Summary Statistics

	Mean	*Minimum*	*Maximum*	*N*
Actual Wage ($ dollars)	4.08 (2.048)	1	32	5086
Log of Actual Wage	1.316 (.408)	0	3.466	5086
Predicted Log Wage	1.258 (.201)	.785	1.722	8610

Note: Standard deviations are in parentheses

Because the dependent variable in the crime participation models is binary, coefficients generated by an Ordinary Least Squares regression model will have the interpretation of increases or decreases in the probability that an individual will participate in criminal activities. Binary dependent variables have discrete distributions, taking on a value of one or zero, creating heteroscedasticity within a linear probability model. Heteroscedasticity occurs when the variance of the disturbance is not constant across the range of the sample. It would be possible to ignore the heteroscedastic residuals and still use OLS to estimate crime participation because the parameter estimators remain unbiased. A better choice is a probit model, which assumes that the disturbance in the model that determines propensity to commit crime follows a standard normal distribution with zero mean and unit variance. Unlike the linear probability model, which utilizes OLS estimation, the probit model uses maximum likelihood estimation. Under this estimation procedure, the probit model chooses coefficient estimates that maximize the log of the probability of observing the actual values of the dependent variable given the values observed for the explanatory variables (e.g. X_i,=demographic, E_i =economic, and C_i =past criminal behavior) in the model. The crime participation probit estimation is shown below.

$$(2) \qquad Prob(illegal\_inc=1 \mid x_i) = \alpha + \beta_3 X_i + \beta_3 E_i + \beta_3 C_i$$

The crime participation model was also estimated using crime-specific binary dependent variables.

Section 5: Results and Interpretation

Tables 4-A and 4-B present estimates of the determinants of crime participation using the illegal income dummy dependent variable. Table 4-A replicates Grogger's restricted sample defined by men not enrolled in school or the armed forces, while Table 4-B uses the full sample.

Column 1 of both tables presents the results of the crime participation probit using actual wage rates reported in the NLSY. The coefficient on log wage in the restricted sample in column 1 (Table 4-A) has the expected negative sign. But, it is insignificant with a z-statistic of –.98. The mean derivative of crime participation with respect to wage indicates that a 10 percent increase in wages would decrease crime participation by .83 percent (In all interpretations of results for wage coefficients, the mean derivative with respect to the log wage is divided by the sample mean of the actual wages, 4.08). The coefficient on log wage in the full sample in column 1 (Table 4-B) has an unexpected positive sign and is also insignificant with a z-statistic of .04. The magnitude of the coefficient indicates that a 10 percent increase in wages would increase crime participation by .015 percent.

Column 2 in both tables presents the results of the crime participation probit that accounts for the endogeneity and partial observance of market wages in the data by using a predicted wage estimator as discussed earlier. The coefficient on log wage in the restricted sample in column 2 (Table 4-A) is negative as predicted, but is also insignificant with a z-statistic of –1.32. The mean derivative of crime participation with respect to wage indicates that a 10 percent increase in wages would decrease crime participation by 2.95 percent. This is somewhat higher than Grogger's estimate of 1.79 percent (For Grogger's full estimation results, see II. Literature Review). The coefficient on log wage in the full sample in column 2 (Table 4-B) is also negative and insignificant with a z-statistic of -.11 The magnitude of the coefficient indicates that a 10 percent increase in wages would decrease crime participation by .96 percent.

Table 4-A
Estimates of the Crime Participation Probit
Sample restricted to men not enrolled in school or the armed forces in 1979 or enlisted in 1980.

Variable	*Crime Participation probit – Log wage (2)*			*Crime Participation probit – Predicted log wage (1)*		
Log Wage	-.116	(.118)	[-.034]	-3.979	(3.022)	[-1.202]
Living in a parental home	.152	(.118)	[.045]	.125	(.108)	[.037]
Age at 1980 interview	-.116	(.029)	[-.034]	.183**	(.227)	[.055]
Black	.092	(.113)	[.028]	-.037	(.115)	[-011]
Hispanic	-.199	(.128)	[-.055]	-.043	(.142)	[-.013]
Urban location	.298*	(.111)	[.082]	.587**	(.303)	[.156]
Charged with a crime before 1979	.493**	(.595)	[.165]	.546**	(.127)	[.188]
Non-wage Income	-8.56e-6**	(4.31e-6)	[-2.52e-6]	-8.40e-6**	(3.88e-6)	[-2.54e-6]
N			1044			1182

Note: Standard errors are in parentheses. Mean derivatives are in brackets.
***=significant at 5 percent level of confidence.*
**=significant at 10 percent level of confidence.*

Table 4-B
Estimates of the Crime Participation Probit
Full Sample

Variable	*Crime Participation probit – Log wage (2)*			*Crime Participation probit – Predicted log wage (1)*		
Log Wage	.002	(.067)	[.0006]	-.169	(1.489)	[-.039]
Living in a parental home	.011	(.070)	[.003]	.054	(.055)	[.012]
Age at 1980 interview	-.083	(.014)	[-.020]	-.054**	(.116)	[-.012]
Black	.117	(.066)	[.029]	.042*	(.053)	[.010]
Hispanic	-.143	(.074)	[-.033]	-.084*	(.069)	[-.019]
Gender=Male	.431*	(.053)	[.102]	.496**	(.274)	[.116]
Urban location	.154	(.065)	[.035]	.192**	(.148)	[.042]
Charged with a crime before 1979	.634**	(.097)	[.193]	.645**	(.079)	[.193]
Non-wage Income	-4.19e-6**	(2.04e-6)	[-1.00e-6]	-3.10e-6**	(1.48e-6)	[-7.18e-7]
N			3817			6554

Note: Standard errors are in parentheses. Mean derivatives are in brackets.
***=significant at 5 percent level of confidence.*
**=significant at 10 percent level of confidence.*

The wage coefficient (in both the restricted and full sample) based on the predicted wage estimator is substantially higher than the wage coefficient based on actual wages, implying that the unobserved determinants of market productivity are positively correlated with the unobserved determinants of criminal productivity. Furthermore, the wage coefficient (using both predicted wages and actual wages) is substantially higher in the restricted sample than the wage coefficient in the full sample. Given the lower wage coefficients in the full sample, individuals in the full sample may have alternatives to leisure other than work and crime.

The remaining coefficients presented in Tables 4-A and 4-B explain how criminal experience and individual characteristics affect the crime choice. The variable used to proxy criminal experience is positive in all model specifications. This binary variable indicating whether the respondent had been charged with a crime is always highly significant. The positive coefficient supports theoretical implications that as in legitimate work, criminals learn by doing.

The coefficient on urban location is positive and significant in all specifications, implying that living in an urban location increases the probability that an individual will engage in criminal activities. Everything else equal, urban locations may make crime more attractive than in rural locations because there are more potential targets for criminals. The coefficient on the male dummy in the full sample is positive and highly significant, implying that being a male increases the probability of committing crime, everything else equal. This is expected given that men commit more crime nominally than women. For example, estimates from the data show that 8.1 percent of male respondents stole something worth more than $50 at least one time in 1980, compared to 2.5 percent of female respondents.

The coefficient on non-wage income is negative and significant. This finding contrasts with Grogger's estimation results, which find the coefficient on non-labor income to be insignificant in all model specifications. In constructing his non-wage income measure, Grogger multiplied the reported fraction of income from crime by the respondent's total income from all sources in 1979. I constructed the measure using the respondent's family's total net income in

1979 and subtracted the individual's total income from all sources in 1979. Mean non-labor income by my construction was $13,414. Grogger estimates mean non-labor income to be $1,188. It should be noted that a respondent's living arrangement could lead to large differences in non-wage income under my construction. Individuals living in a parental household might have a larger non-wage income than individuals living independently because the parent's income will be included in total net family income. But, in the crime participation probit, I have controlled for type of residence. Therefore, holding everything else constant, increasing an individual's non-wage income by $1,000 decreases the probability of committing crime by .08 – .23 percent.

Tables 5-A and 5-B present estimates of the determinants of crime participation using crime-specific dummy dependent variables. Table 5-A replicates Grogger's restricted sample defined by men not enrolled in school or the armed forces, while Table 5-B uses the full sample. All model specifications use predicted wages based of the reduced form wage equation.

The signs of the coefficients on log wage in the restricted sample (Table 5-A) are all negative, except selling marijuana and burglary. In all activities, except stealing something worth more than $50 and gambling, none are significant, suggesting that wage may not be a good indicator of activity specific crime participation. This finding contrasts with Grogger's results, which estimated positive coefficients on log wage in every activity.

In the original data, the crime-specific variables were ordered, giving a measure of the level of crime participation for each activity. Possible responses ranged from committing the illegal activity once, twice, 3-5 times, 6-10 times, 11-50 times or more than 50 times. Estimating crime participation using an ordered probit model, which accounts for the multiple, discrete categories within the variable and generates the predicted probabilities of moving from one category to another, yields similar results. The signs of the coefficients on log wage are the same and none are significant. But, estimating crime participation using the ordered probit model in the full sample, yields highly significant, positive coefficients on log wage, contrary to the predictions of the theory.

The coefficients on log wage in the full sample (Table 5-B) are also mixed. The coefficient of log wage is negative for gambling, while the other property crimes estimated are positive. The coefficients on all activities except gambling are insignificant.

Section 6: Extensions to the Model

To test the theoretical implications of my model further in terms of the effects of increases in criminal sanctions on crime participation, I incorporate information gathered from the 1982 Employment and Expenditures Report of the Bureau of Justice Statistics. Specifically, I use law enforcement spending by state to proxy criminal sanctions or the probability that an individual will be arrested (The data does not include expenditures on the state's court systems or correctional facilities). I hypothesize that, similar to wages in legitimate jobs, increases in the certainty of criminal sanctions will decrease the probability that an individual will commit crime.

To estimate the model, I use the crime participation probit with the criminal income measure as the dummy dependent variable, while adding a measure of per capita law enforcement spending. The variable was constructed by dividing total state law enforcement expenditures by the state population. Unfortunately, data limitations required that both measures be taken from 1982. Similarly, I constructed per capita measures of police protection expenditures, all of which are shown below in Table 6.

Table 6
State Expenditure Summary Statistics

	Mean	*Minimum*	*Maximum*	*N*
Per Capita Law Enforcement Expenditure	1.483 (.652)	.897	8.161	10261
Per Capita Police Protection Expenditure	.996 (2.244)	.243	14.925	9819

Note: Standard deviations are in parentheses.
** Data was extracted from the Bureau of Justice Statistics - 1982 State Employment and Expenditures Report.*

Measures of law enforcement and police protection expenditures are likely to be highly correlated. Initial estimations of the model using per capita general law enforcement expenditures produced highly significant coefficients, while coefficients on per capita police protection expenditures were insignificant at even 20 percent level of significance. Both coefficients had the unexpected positive sign. Thus, per capita law enforcement spending will be used in the model specification. The sample is restricted to men who were not enrolled in school or the armed forces in 1979 and did not enlist in the armed forces in 1980.

Table 7 presents the estimates of the crime participation probit with (column 2) and without (column 1) a measure of certainty of criminal sanctions.

Table 7
Estimates of the Crime Participation Probit using state-level law enforcement data.
Sample restricted to men not enrolled in school or the armed forces in 1979 or enlisted in 1980.

Variable	***Crime Participation probit (1)***			***Crime Participation probit – Using state-level data (2)***		
Predicted Log Wage	-3.979	(3.022)	[1.202]	-3.510	(3.109)	[-1.069]
Living in a parental home	.125	(.108)	[.037]	.103	(.111)	[.031]
Age at 1980 interview	.183**	(.227)	[.055]	.152	(.234)	[.046]
Black	-.037	(.115)	[-011]	-.038	(.118)	[-011]
Hispanic	-.043	(.142)	[-.013]	-.075	(.146)	[-.022]
Urban location	.587**	(.303)	[.156]	.534*	(.311)	[.145]
Charged with a crime before 1979	.546**	(.127)	[.188]	.576**	(.130)	[.200]
Non-wage Income	-8.40e-6**	(3.88e-6)	[2.54e-6]	-7.36e-6*	(3.99e-6)	[-2.24e-6]
Per Capita Law Enforcement Expenditure				.094**	(.045)	[.014]
N			1182			1098

Note: Predicted log wages are used in both model specifications.
Standard errors are in parentheses. Mean derivatives are in brackets.
***=significant at 5 percent level of confidence.*
**=significant at 10 percent level of confidence.*

The coefficient on per capita expenditure has an unexpected positive sign and is highly significant with a z-statistic of 2.12. The coefficient indicates that, holding everything else constant, increasing per capita spending on law enforcement by $1 increases the probability of committing crime by .14 percent. Estimating the model using the full sample produced similar results. These coefficients should not be interpreted as evidence that increased law enforcement spending causes more crime. Rather, interpretations of the coefficient may imply that increasing enforcement spending allows agents to detect more crime. Secondly, consistently high-crime areas are more likely to have increased law enforcement expenditures. In this case the relationship between spending and crime participation indicates correlation, but not necessarily causation. The coefficient on log wage (column 2) remains negative and insignificant with the addition of the expenditure measure. However, the coefficient on log wage decreases in the expanded model specification.

Next, I use the estimates yielded in the extended crime participation probit model to predict the effects of increasing an individual's legitimate labor opportunities with the effects of increasing the certainty of criminal sanctions in reducing crime participation. Using population and labor force participation information from the 1980 United States Census, I estimate that increasing every male civilian labor force participant's wage rate by $1 would require $25,380,517,520. This cost estimate was generated by multiplying the total number of men, ages 16-24, in the civilian labor force in 1980 (14,523,629) with the average hours worked per year (1,987.85) and the employment rate (87.82 percent) of the sample. To calculate the effect of the predicted probability that an individual will commit a crime of increases in legitimate labor opportunities, I held each of the model parameters fixed and increased the wage ($4.08) by $1 to $5.08. The results of the prediction are shown below in Table 8.

Table 8
Predicted effects of increases in labor opportunities

	Mean	*Minimum*	*Maximum*	*N*
Predicted Probability of a positive outcome wage=$4.08	.224 (.126)	.015	.883	7459
Predicted Probability of a positive outcome wage=$5.08	.072 (.061)	.002	.663	7459
Difference in Predicted Probabilities	-.152 (.068)	-.300	-.013	7459

Note: Standard deviations are in parentheses.

The difference in predicted probabilities indicates that raising an individual's wage offer in the legitimate labor market by $1 would decrease crime participation by 15.2 percent.

Alternatively, the cost of increasing wage offers by $1 could also be applied to increases in law enforcement expenditures or increases in the certainty of criminal sanctions. Dividing the total cost of the wage increase ($25,380,517,520) by the total U.S. population in 1980 yields $112.03 per person. The predicted probabilities resulting from the increased per capita law enforcement spending are shown below in Table 9.

Table 9
Predicted effects of increases in criminal sanctions

	Mean	*Minimum*	*Maximum*	*N*
Predicted Probability of a positive outcome Base per capita spending	.393 (.157)	.043	.843	6259
Predicted Probability of a positive outcome Base spending plus $112.03	1 (0)	1	1	6259
Difference in Predicted Probabilities	.607 (.157)	.157	.957	7459

Note: Standard deviations are in parentheses.

Taken together, the results presented in Table 8 and Table 9 show the predicted effects on crime participation based on the same cost estimate.

Kathleen E. Wirth

RTI International

3040 Cornwalis Rd.

P.O. Box 12194

Research Triangle Park, NC 27709

kwirth@rti.org

References

Blau, David M (1987). "A Time-Series Analysis of Self-Employment in the United States." *Journal of Political Economy* 95: 445-467.

Fagan, Jeffery (1992). "Drug selling and illicit income in distressed neighborhoods: the economic lives of street-level drug users and dealers." *Drugs, Crime and Social Isolation: Barriers to Urban Opportunity*. Eds. George E. Peterson and Adelle V. Harrell. Washington D.C.: Urban Institute Press. 99-146

Fairlie, Robert W(2002). "Drug Dealing and Legitimate Self-Employment." *Journal of Labor Economics* 20.

Fields, Allen B (1986). "Weedslingers: Young Black Marijuana Dealers." *Teen Drug Use*. Eds. George Beschner and Alfred S. Friedman. Lexington, MA: Lexington Books. 84-104.

Freeman, Richard (1999). "The Economics of Crime." *Handbook of Labor Economics*. Ed. O. Ashenfelter and D. Card. New York: Elsevier Science B.V. 3529-3571.

Grogger, Jeffery (1997). "Market Wages and Youth Crime." *Journal of Labor Economics* 16: 756-791

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

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

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