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ON THE DYNAMIC DECISION TO PARTICIPATE IN CRIME

by

JENNY WILLIAMS

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ABSTRACT

ON THE DYNAMIC DECISION TO PARTICIPATE IN CRIME
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JENNY WILLIAMS

Our research examines the decision to participate in crime using a dynamic model of individual choice under uncertainty. The motivation for studying this decision in a dynamic framework is twofold. First, it allows us to formulate a theory of rational criminal choice, where agents anticipate the future consequences of their decisions. Second, it permits explanation of the temporal pattern displayed in aggregate arrest data. Across different countries, cities, and time periods, the aggregate arrest rate is a unimodal and positively skewed function of age. The standard static approach to crime offers no insight into the cause of this empirical regularity.

We study criminality in a dynamic context by introducing social capital into the economic theory of crime. Social capital measures the extent to which an individual is bonded to legitimate society. The social control theory of crime posits that bonds to society strengthen as the individual ages, increasing the cost of deviant behavior, making criminal acts less likely. This hypothesis is consistent with the temporal pattern displayed in aggregate arrest data. In our formulation, preferences and legitimate income depend on the individual's stock of social capital. Rationality is imposed by requiring agents to take these effects into account.
We empirically implement our model using panel data on a sample representative of young men in urban areas of the United States. Estimation is complicated by an omitted regressor problem, which arises because there are two possible future states - apprehension and escaping apprehension. Only one state is realized for each individual and subsequently observed by the econometrician. However, the unobserved choices in the state not realized enter the Euler equations. We resolve this problem by replacing the unobservables with Monte Carlo draws from the conditional empirical distribution of observed outcomes and using a Simulated Method of Moments estimator.

Our results provide evidence in support of a social capital theory of crime. We find that social capital affects both preferences and earnings in the legitimate sector. Further, as predicted by social control theory, social capital becomes increasingly important over the life-cycle. This raises the cost associated with crime, making its occurrence less likely.
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CHAPTER 1

INTRODUCTION

"...the root cause of crime — criminals."

Bob Dole, Republican Presidential Candidate, 1996

According to a recent Gallop poll, Americans consider reducing crime to be the country’s foremost priority. Crime ranked above cutting the budget deficit, with 84% of those surveyed rating tougher anti-crime legislation as the top priority compared with 82% believing similarly about reducing the deficit. One need only look to the 1996 presidential campaign to appreciate the depth and breadth of the American public’s concern with crime. It has prompted Democrats to set aside their traditional position and embrace what had been a Republican approach. Clinton has endorsed expanding the federal death penalty, limited death row appeals, spent billions of dollars on prison construction, and included the $8.8 billion COPS program, designed to put 100,000 additional police officers on the street, in the anti-crime bill enacted in 1994. During the 1996 campaign, Clinton has emphasized crime as the central pillar of his presidency1. For his part, Dole has declared America a “nation paralyzed by crime”, and if elected, vows to “make the life of violent criminals hell.”2 While crime may have considerable political resonance in the battle to be

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President of the United States of America, the battle against crime is largely the responsibility of state and local governments.

The response of State legislatures to demands for tougher anti-crime laws has been in the form of bills establishing mandatory minimum sentences for various crimes. Among the more high profile of these bills is California’s ‘three strikes’ law. This law guarantees extended sentences for repeat offenders. If fully implemented, California’s ‘three strikes’ law will reduce serious crimes by approximately 21% (Greenwood, et al., 1996). The price tag associated with this reduction in crime is estimated to be 5.5 billion dollars per year. This represents an increase in California’s criminal justice system operating costs of more than 100% (Greenwood, et al., 1996). The ‘three strikes’ legislation has come at a time when the nation’s state and federal prison population is burgeoning. This year, state and federal prisons experienced the largest one year population increase ever, with the number of inmates increasing by 84,404 during the twelve months ending June 30, 1995. At the end of June, there were 1.5 million adults incarcerated in the United States. Since 1980, when the mandatory minimum sentence bills began to appear, the total number of people held in federal and state prisons and locals jails has almost tripled, growing at an average annual rate of 7.9%. With the cost of incarnation estimated to be $21,000 per prisoner per year, not including construction costs, the sheer expense of the ‘three strikes’ law makes it unlikely to be fully implemented; reducing the budget deficit is the number two concern among Americans.

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4 Welch, R. S., Chief, California Offender Information Services Branch; memorandum, March 14, 1994.
The cost of crime policies which rely solely on deterrence and incapacitation have led policy makers to seek more cost effective alternatives. A recent study by Peter Greenwood et al. at the RAND Corporation considers measures that involve early intervention in the lives of people who are at risk of pursuing criminal careers and compares their cost effectiveness to the 'three-strikes' law. The RAND study shows that crime could be reduced through three out of the four programs considered; parent training, graduation incentives, and supervision of delinquents. Greenwood et al. estimate that the combination of graduation incentives and parent training would bring about the same reduction in crime as the 'three strikes' law at a total cost of 1 billion dollars per year (compared to 5.5 billion for the 'three strikes law'). This is based solely on program costs and does not take into account savings from averting individuals from criminal careers, such as incapacitation costs. They also find the cost effectiveness of these programs to be robust with respect to variations in assumed parameters.

The RAND study focuses on using preventative policies to influence individuals' potential criminal behavior. In doing so, it goes beyond the issue of what causes crime, and raises the question of what causes criminals. Of particular interest to economists and policymakers alike is understanding the mechanisms by which preventative policies affect criminal behavior. To date, the economics literature has primarily concerned itself with policies based on deterrence and incapacitation. We hope to go part of the way in addressing the broader question of the cause of criminality in the research that follows.
Our research takes a structural approach to examining the decision to participate in crime within a life-cycle setting. The motivation for considering the crime participation decision in a dynamic framework is twofold. First, it allows us to formulate a theory of rational criminal choice, where agents anticipate the future consequences of their decisions. Relating current period decisions to future outcomes is an essential feature of a model which seeks to understand the mechanisms by which preventative policies may work. The second reason for moving to a dynamic setting is the empirical regularity of the age-crime profile. The age-crime profile refers to the relationship between aggregate arrests and age. Across different countries, cities, and time periods, the aggregate arrest rate is a unimodal and positively skewed function of age. This temporal pattern of behavior is not addressed in the standard static approach to crime.

To study criminality in a dynamic context, we allow preferences and legitimate income to depend on the individual’s stock of social capital. Social capital measures the degree to which an individual is attached to the legitimate community. It enters the model in a manner consistent with the basic premise of social control theory: ceteris paribus, crime is more costly (and therefore less likely) for those who are tightly bonded to their community. In our formulation, social capital affects both preferences and future wages. Rationality is imposed by requiring agents to take these future effects into account. This approach is consistent with a model which conceives of preventative policies working through social capital accumulation to reduce the likelihood of criminality.
We empirically implement our model of individual choice using data from the 1958 Philadelphia Birth Cohort Study (Wolfgang, Figlio and Tracy, 1988). This data presents a unique opportunity to study the dynamic decision to participate in crime. Data used to study crime at the individual level are generally drawn from high risk populations, such as prison releasees, and consequently suffer from selection bias. The 1958 Philadelphia Birth Cohort Study has a universe of all individuals born in 1958 who lived in Philadelphia at least from their tenth until their eighteenth birthday. Juvenile and adult arrest records up to age 26 were collected for these persons. The cohort was then stratified and a random sample taken for a retrospective follow-up survey. The follow-up survey sample is used to create annual observations on 500 men for the period 1977 to 1982. Since all individuals in the sample are the same age and lived in the same city during their adolescent years, this data set is especially suited to studying dynamic elements of individuals' preferences.

In our model, estimation of the Euler equations is made problematic by an omitted regressor problem. This issue arises because there are two possible future states: apprehension and escaping apprehension. Only one state is realized for each individual and subsequently observed by the econometrician. The unobserved choices in the state not realized enter the Euler equations, causing an omitted regressor problem for estimation of the moment conditions. We will resolve this issue by replacing the unobservables with Monte Carlo draws from the conditional empirical distribution of
observed outcomes. We then use this data to form a simulator of the moment condition. Estimates of the Euler equations can then be obtained minimizing the generalized distance of the simulated moments from zero.

The results from applying the Method of Simulated Moments to our system of Euler equations provides evidence in support of our social capital formulation of social control theory. It also provides rich insights into the timing and mechanisms through which individuals make the transition from childhood to adult members of their legitimate community.
CHAPTER 2

LITERATURE REVIEW

This chapter is not intended as a review of the literature on the economics of crime. Indeed, the task of surveying this substantial body has been the subject of several books (Heineke, 1978; Schmidt and Witte, 1984; Eide, 1994). The purpose of this chapter is to motivate the model developed and estimated in the following chapters within the context of the literature. Since ours is an applied work, we discuss the theoretical literature in terms of the testable hypotheses it has produced. Of particular interest is the crime-work nexus as an explanation of the cause of criminality. We focus on the empirical literature as it relates to this issue and use its insights as a guide to what we believe to be a more fruitful approach.

2.1 A Brief History of the Economics of Crime

The starting point for any discussion of the economics of crime is the seminal work on crime and punishment by Becker (1968). Becker’s model has provided the framework and focus for most subsequent studies in the economics literature. Using a model of individual choice under uncertainty, Becker derives a deterrence function which relates the number of offenses to the probability and severity of punishment. The government chooses the level of punishment for offenses and the expenditure on the police and hence the punishment to minimize a social loss function. Losses include damage from offenses,
expenditure on police, and costs of punishment. Ehrlich (1973) extends Becker’s model to one of time allocation and derives comparative static results which have become the basis for testing the economic model of crime. Ehrlich’s model predicts that a relative increase in legal wages will reduce the incentive to participate in illegal activity; an increase in either the probability of apprehension and conviction or punishment if convicted reduces the incentive to participate in crime; and the deterrent effect of an increase in the marginal or average penalty per offense will exceed the effect of a similar increase in the probability of apprehension and punishment if the offender is a risk avoider.

Hindered by a lack of individual level data, the first generation of empirical research in crime sought to test Ehrlich’s predictions using the available aggregate data. Most of these studies use a set of simultaneous equations for the crime rate and some measure of sanctions to determine the deterrent effects of law enforcement, working through the probability of apprehension and severity of punishment, on the aggregate level of crime. The focus of this literature is the development of optimal public policies to combat illegal behavior. Policy instruments are confined to those which influence the certainty and severity of punishment. This macroeconomic approach suffers from problems of aggregation and model identification, making interpretation of empirical findings difficult. The Panel on Deterrence and Incapacitation severely criticized studies of crime based on aggregate data (Blumstein, Cohen, and Nagin, 1978) and cited a need for increased behavioral and statistical modeling at the individual level of analysis. While society’s ultimate interest in crime policy may be its effect on the aggregate crime rate, such policies
work through influencing individual criminal behavior. Therefore, the Panel reasoned, crime should be studied at the individual level.

During the eighties, studies of crime using the individual as the unit of analysis started to appear. Many of these studies continued in the vein of their macro predecessors, seeking to test the deterrence hypothesis derived by Ehrlich. Typically, this was done by modeling recidivism in prison releasees using simultaneous Tobit models (Sickles, Schmidt, and Witte, 1979), or hazard functions (Schmidt and Witte, 1988). Alternatively, this new generation of research focused on testing the labor market predictions of the economic model of crime. This was achieved by modeling the reduced form effect of juvenile or adult arrests on employment and earnings (Good, Pirog-Good, and Sickles, 1986; Good and Pirog-Good, 1987; Grogger, 1995). Individual level data are generally only available for high risk groups such as prison releasees or juvenile delinquents. The information on criminal behavior typically comes from individual criminal histories maintained by the criminal justice system for people who have a criminal record. These criminal histories are commonly referred to as rap sheets. Since rap sheets only report those crimes resulting in an arrest, they provide a systematically biased sample of crimes actually committed.

Tauchen, Witte, and Greisinger (1988) provide the first estimates of criminal activity for a general population using panel data. While many of the studies using individual level data suffer problems of sample selectivity and incomplete observation of variables of interest, they nonetheless, provide sufficient evidence to question the mechanisms by which crime and work are related in the traditional economic model of crime.
Ehrlich’s model predicts that a relative increase in legal wages will reduce the incentive to participate in illegal activity. Consequently, we expect to observe that criminals earn a lower wage and spend less time working compared to noncriminals. Interestingly, empirical work has provided little support for a significant relationship between wages, unemployment, or income, and crime, while finding strong evidence of an inverse relationship between criminal activity and employment. Witte (1980), using information on a sample of men released from the North Carolina prison system, reports that legal wages have a generally insignificant effect on criminal activity. Thornberry and Fanworth (1982) conclude that earnings are not significantly related to criminality. The absence of income effects contrasts with their finding that other measures of the individual’s social status are significant for explaining involvement in crime. Tauchen, Witte, and Griesinger (1988) find that crime does not serve mainly as a direct source of income and that incentive effects from higher wages are not very strong. Witte and Tauchen (1994) also find little evidence that wages or income have a consistently significant effect on crime. Grogger (1995), analyzing employment data for men arrested in California from 1980-1984, finds that most of the correlation between arrests and earnings is due to unobserved heterogeneity. Schmidt and Witte (1984) find that wage rates are not significantly related to criminal activity. Long and Witte (1981), Freeman (1983, 1991), and others have found neither wages nor income to have a consistently significant affect on crime. While Freeman (1991) reports that men involved with crime are less employed than others, the
low rate of employment was not the result of aggregate labor market conditions. Rather, it was the result of their involvement in crime.

Despite the lack of evidence of a significant relationship between hourly earnings, income, or unemployment, and crime, the empirical literature finds that greater time spent working is associated with less crime. Freeman (1987), in studying inner city black male youths from high poverty neighborhoods, finds a significant inverse relationship between employment and crime. Tauchen, Witte, and Greisinger (1988) and Witte and Tauchen (1994) find that greater time working is associated with a lower probability of criminal activities. Studies by Farrington et al. (1986), Gottfredson (1985), and Viscusi (1986) have also found employment has a negative effect on criminal activity.

Freeman (1987) makes an interesting point with regard to the relationship between crime and work. While there is a significant inverse relationship between the two activities, crime and employment are not mirror images of one another. In Freeman's study, education, marriage, and church attendance have a positive effect on employment, while measures of drinking, drugs, and marijuana usage have no effect on employment. In contrast, Viscusi (1986) finds that education is only weakly inversely related to crime and that drinking, drugs, and pot use are highly correlated with crime. Further, Witte and Tauchen (1994) report that educational attainment is not significantly related to the number of arrests.
The picture that emerges from these studies is that labor force participation is associated with less criminal activity while the level of the legal wage has no affect. These stylized facts are not consistent with the predictions of the type of models of crime adopted in the economics literature. Another characteristic of crime inconsistent with the static time allocation approach is the temporal pattern displayed in aggregate arrest data. This phenomenon, known as the age-crime profile, is well documented in the sociology and criminology literature, and has recently gained a place in the economics literature.

More than 150 years ago, Quetelet (1984,[1831]), using French cross sectional data, discovered that the arrest rate rose rapidly from the teen years to reach a maximum in the early twenties and then steadily declined. This relationship, referred to as the age-crime profile, has become the most firmly established empirical regularity in the criminology literature (Hirschi and Gottfredson, 1983; Wolfgang, Thornberry and Figlio, 1987). A large number of studies in criminology and sociology have found the unimodal and positively skewed age-crime relationship to be stable across countries, cities, and time periods. The shape of the age-crime profile is determined by both the participation rate and intensity of offending. The empirical evidence implies that either the participation rate, the intensity of offending, or both must diminish with age. In order to explain this type of temporal pattern, it is necessary to consider crime in a dynamic framework.
Several studies in economics have sought to address the temporal pattern of behavior displayed by the age-crime profile. Flinn (1986) extends the economic model of crime to a dynamic setting by incorporating human capital formation. In the tradition of Ehrlich, Flinn's model is a time allocation model, where the amount of time to be allocated between crime and work is net of leisure. Since human capital is accumulated at work, crime takes away from time spent working and therefore diminishes the amount of human capital accumulated. A lower stock of human capital reduces future wages and hence, time spent working. As crime and work are substitutes, less time spent working translates to an increase in participation in criminal activities. Flinn's model suggests that human capital formation decreases crime directly because it increases wages. The lack of empirical evidence regarding a negative relationship between wages and crime casts doubt on the ability of human capital theory to explain criminal activity.

Leung (1994) and Bearse (1995) develop representative agent models of criminal behavior that are dynamic in nature. Leung (1994) assumes no recidivism and that all individuals with no prior arrests engage in crime. These assumptions lead to a monotonically decreasing age-participation profile. The effects of a finite lifetime, combined with a severity of punishment that decreases with age, imply that the frequency with which individual's commit crimes increases monotonically over time. Leung shows via numerical example that the tension of these two effects can produce a hump-shaped age-arrest

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5 In Appendix 1 we reformulate Ehrlich’s model as a dynamic programming problem by allowing individuals to accumulate human capital.

6 In Chapter 5, we provide evidence that the human capital approach to crime is unlikely to be fruitful.
profile. Bearse (1995) points out that the no recidivism assumption is not applicable to the bulk of felony crimes and if relaxed, the model would not necessarily predict a hump-shaped age-crime profile. He shows that a hump-shaped age-arrest profile can be generated without assuming no recidivism. Bearse posits a model in which an individual's lifetime utility is an additively nonseparable function of the payoffs to crime, and the hazard rate of arrest depends on his arrest history. The specification for lifetime utility allows risk aversion to increase with age. Since crime is a risky activity, the individual will tend to commit fewer crimes as he ages. The hump-shaped age-arrest profile results from the tension between participation and intensity which tend to fall with age, and a hazard rate of arrest that tends to rise with age. While both the Leung and Bearse models of crime are dynamic, they offer no testable hypotheses as to the cause of criminality. To generate the hump-shaped age-crime profile in their numerical examples, both researchers assume all individuals participate in crime in the initial period.

2.2 An Alternative Approach

If empirical evidence does not support a theory in which low wages cause criminal behavior, does it provide an alternative explanation? Several researchers have offered such insights. Freeman (1991) suggests the economic model is limited in its ability to explain crime due to omission of peer influences, attitudes towards crime, childhood upbringing, and so forth. Similarly, Witte, and Tauchen (1994) suggest that their results "might be consistent with a model of criminal activity that conceives of legitimate time uses and social associations (e.g., participation in church activities, white collar
employment) as shaping or revealing preferences concerning illegal activities." Tauchen, Witte, and Greisinger (1988) find evidence of preference or informational effects, indicating that participating in legally orientated activities serves to lessen criminal activity and participating in illegal activity serves to stimulate it.

Let us consider the evidence these researchers provide regarding the manner in which information, time use, and an individual's associates affect criminal behavior. Tauchen et al. (1988) find attending a parochial junior or senior high school to be significantly related to lower levels of criminality. Viscusi (1986) finds church attendance to be associated with lower levels of reported participation in criminal activity. Also, Freeman (1986) finds that church attendance is a significant determinant of who escapes inner city poverty. Tauchen et al. (1988) conclude from this evidence that their findings are consistent with the primary effect of parochial schooling operating through preferences or informational effects, such as networking. They deduce that work, like schooling, may reflect individuals preferences or shape them in ways that are not conducive to criminal activity. Also, working or being at school may provide information conducive to legal activities -- or not conducive to illegal ones. Witte (1995) suggests that education may have a role to play in imparting information about the rules of the game, that is, what is legal and moral, or benefits of legal activities and costs of illegal ones. Investigating the effects of other potential preference revealing variables, Tauchen et al. (1988) report that the coefficients on race, socioeconomic status of parents, number of addresses during high school years, average income of the family neighborhood, and the ethnic background of
the family neighborhood are not consistently significant across specifications. However, they do find that boys who had more police contacts as juveniles, whose first arrest was for a serious crime against persons, and who were gang members as juveniles show higher crime rates as young adults. From this, they infer that just as schooling and work shape preferences in a manner not conducive to criminal activity and provide information about legal endeavors, gang membership and a more substantial record lead to criminal preferences and information about illegal endeavors.

It is no coincidence that researchers in economics have arrived at these conclusions. Such factors as success at work and belief in conventional values are predicted to exert a negative effect on criminal involvement in social control theory. Social control theory posits that an individual's bonds to legitimate community restrain his potential criminal behavior. In adulthood, the factors which build bonds to society include the institutions of employment and marriage. However, the process by which these bonds are created begins prior to adulthood. In childhood, it is the institution of family that builds bonds to conventional society. Our research uses social control theory to provide a framework to represent the hypotheses put forward by Freeman (1986), Tauchen et al. (1988), and Witte (1995) regarding the role of information and preferences in the decision to participate in crime. Before presenting our model, we provide a brief discussion of social control theory.
Social control theory assumes that everyone is motivated to commit crime, but most are kept from doing so by controls which are enforced by social sanctions. It is the bonds to conventional social groups that generate the controls that restrain misbehavior. A derivative of social control theory is informal social control theory, which emphasizes the influence of institutional relationships such as family, work, and community on the likelihood of deviance. An empirical literature supports informal control theory, finding evidence of deterrent effects of moral and social sanctions on deviant behavior (Gottfredson and Hirschi, 1990). Laub and Sampson (1993) link informal social control with the notion of social capital. Social capital consists of three components: networks for disseminating and obtaining information (e.g. about job opportunities), a reward and punishment system, and a system of reciprocal debts and obligations (Coleman, 1988). It measures the degree to which an individual is bonded to society, and as with any other kind of capital, it is cumulative. Laub and Sampson (1993) stress the role of stable attachment to the labor force and a cohesive marriage in the accumulation of social capital in adulthood.

Prior to adulthood, it is the institution of family that builds bonds to conventional society. As noted by Becker (1991), the fortunes of children are linked to their parents through endowments, such as family reputation and connections, knowledge, skills, and goals provided by the family environment. Family social capital is the vehicle by which intergenerational transmission of human capital,
norms, and values take place. Since it embodies the relations between children and parents, social capital of the family depends on physical presence of the parents and on the attention given to the child by the parents. Even if both parents are physically present, a lack of social capital can result from the child's embeddedness in a youth community, such as a gang, or a dilution of adult attention to the child due to the presence of siblings (Coleman, 1988).

The model of informal social control predicts that people who are more attached to the labor force and have a cohesive marriage are less likely to engage in crime. Further, it suggests that characteristics of an individual's family background, such as presence of both parents and gang affiliation, may affect adult earnings (through intergenerational transmission of human capital) and criminal activity (through transmission of norms). Since we have already discussed empirical evidence of the inverse relationship between work and crime, we end our discussion of social control theory with a summary of the evidence regarding the influence of family background on criminality.

In their extensive review of the literature on participation in crime, Visher and Roth (1986) find that family structure is a determinant of criminality. People who lived with one natural parent as children have a higher participation rate in crime than those who lived with both parents. Families with large numbers of children contribute a disproportionately large number of criminals. Family break-ups during
childhood increase participation in crime as adults, with divorce and separation having a stronger adverse effect than death. The studies reviewed by Visher and Roth show a strong empirical relationship between criminal participation and the quality of the subjects’ relationship with their parents. Antisocial behavior in earlier generations has a strong association with participation in crime. In particular, there is a positive association between criminal participation by parents and their offspring. Other factors associated with participation in crime include involvement with negative peers around the age of fourteen and drug use.

Empirical evidence from the economics literature on crime, in addition to evidence from sociology and criminology, suggests social control theory may provide an explanation of the cause of criminal behavior. We explore and test the implications of social control theory by incorporating the social capital formulation into the economic model of crime. Integrating social capital into the economic model of crime results in a theory which is compelling for both theoretical and empirical reasons. From a theoretical perspective, the integrated approach extends the economic model of crime to a dynamic setting in a natural way; by permitting individuals to accumulate a form of capital. It also allows us to impose rationality in the sense that agents anticipate the future consequences of their actions. From an empirical perspective, this formulation provides a life-cycle explanation of crime which is consistent with the phenomenon of the age-crime profile. Of course, the most appealing aspect of integrating social capital into the economic model of crime is that it
places social control theory in a testable framework. In the next chapter we formalize social capital theory by incorporating it into a traditional time allocation model of crime.
CHAPTER 3

A DYNAMIC MODEL OF CRIME

The basic premise of the economic model of crime is that people, including criminals, behave rationally. Specifically, they act in a way calculated to maximize their economic welfare. This idea hails back to Bentham (1970 [1789]) and Beccaria (1963 [1764]), and has more recently been formalized by Becker (1968) and Ehrlich (1973). In this framework, a person commits an offense if the expected utility to him exceeds the utility obtained by using his time and other resources in alternative activities. Therefore, according to the rational choice perspective, some people choose to engage in crime while others choose not to because their benefits and costs - not their basic motivations - are different (Becker, 1968).

Traditionally, the theoretical implications of rationality are analyzed in a static individual choice model. This model views the individual as deciding how to optimally allocate resources, referred to collectively as time, between legitimate and criminal activities. Since costs and benefits are converted to their monetary equivalents, criminal activity is similar to employment in that it requires time and produces income (Ehrlich, 1973). The only way in which crime is distinguished from employment in this type of model is that net income from crime has a state contingent component. The two states of the world are apprehension and escaping apprehension. If an individual is successful in escaping
apprehension, he reaps the entire value (pecuniary and monetary equivalent of nonpecuniary income) of his illegitimate activity. If apprehended, his income will be reduced by a fine which is the monetary equivalent of the punishment meted out. This type of static microeconomic model of crime is primarily used to gain insights into macroeconomic policy issues.

The model developed in this section extends the economic theory of crime to a dynamic setting. This is achieved in a natural manner by integrating the idea of social capital into the traditional time allocation model. In our formulation, social capital affects both preferences and future wages. In part, social capital represents reputation and social acceptance. This has a utility value to the individual. Social capital includes the networks that are built up at work and in the community. These networks serve to, for instance, disseminate information about opportunities for advancement in the legitimate sector. Li (1988) and DeGraaf and Flap (1988), show that informal social resources are used instrumentally in achieving occupational mobility in the United States and, to a lesser extent, in West Germany and the Netherlands. We captured this effect by allowing the accumulation of social capital to raise market wages. In breaking the law, an agent risks a reduction in his social capital since an arrest entails a social sanction. The sanction is assumed to be increasing in social capital. This specification is consistent with the basic premise of social control theory: ceteris paribus, crime is more costly (and therefore less likely) for those who are tightly bonded to their community. Unlike the traditional time allocation model of crime, we do not consider the monetary equivalent of the punishment.
This omission is a result of data limitations. The Philadelphia Cohort Study contains arrest data, but no information on convictions or punishments.

Whether a social sanction is to be imposed is uncertain; it depends on whether the individual is apprehended. We build this uncertainty into the model by making use of a common generalization about the nature of crime. Crime is characterized as providing immediate rewards, while punishment is seen as uncertain and in the distant future. This stylized fact is incorporated into our model by temporally separating the commission of crime from the incidence of the expected punishment. Crimes committed in the current period will be punished next period with probability, \( p \). This assumption imposes the following timing of events: At the beginning of each period, the representative agent must decide on his level of consumption and the amount of resources to spend in work, in crime which produces utility, in crime which produces income, and in leisure. Pecuniary rewards from income producing crime are certain since, by assumption, they depend only on the amount of resources devoted to this activity. In reality, there may be many sources of uncertainty in the returns to crime, such as varying degrees of self protection by potential victims. For analytical simplicity we abstract from these issues. Income from legitimate endeavors depends on both current period resources devoted to it and the level of social capital accumulated by the individual. Since the state of the world - apprehended for last period's crime, or escaped apprehension for last period's crime - and therefore the individual's level of social capital, is revealed at the beginning of each period, legitimate income in the current period is also certain. However, future wages in the legitimate
sector depend on future levels of social capital, which are uncertain. Uncertainty about future welfare is also introduced via the direct utility effect of social capital.

Agents are assumed to be rational in the sense that they anticipate the future consequences of their decisions. Each period the agent must choose his level of consumption of the composite market good, $X_t$, and the amount of time allocated to four possible activities. The individual can spend time in two income generating activities, legal income generating activity, $L_t$, and illegal income generating activity, $C^I_t$, and two utility generating activities, leisure, $l_t$, and consumption generating criminal activity, $C^C_t$. Utility of an individual at any point in time depends on consumption of the composite market good $X_t$, the level of leisure, $l_t$, the amount of time spent in consumption generating crime, $C^C_t$ and the stock of social capital, $S_t$. At time $t$, utility is given by:

$$U(X_t, l_t, C^C_t, S_t).$$

The utility function, $U(.)$ is twice differentiable, concave, and increasing in its arguments. Denoting earnings within a period in terms of the composite good, $X_t$, the intertemporal budget constraint is given by:

$$A_{t+1} = (1+r)(A_t + W_L(l_t, S_t) + W_C(C^I_t) - X_t)$$
where $W_L(L_t, S_t)$ is income from legitimate activity and $W_C(C_t)$ is income from illegitimate activity. We assume that income from legitimate and illegitimate activities are increasing in their respective arguments, so that:

$$\frac{\partial W_L(L_t, S_t)}{\partial L_t} > 0, \quad \frac{\partial W_L(L_t, S_t)}{\partial S_t} > 0, \quad \frac{\partial^2 W_L(L_t, S_t)}{\partial L_t \partial S_t} > 0, \quad \frac{\partial W_L(0, S_t)}{\partial L_t} = 0, \quad \frac{\partial W_C(C_t)}{\partial C_t} > 0.$$  

Recall that social capital includes the networks that are built up at work and in the community which serve to disseminate information about opportunities for advancement in the legitimate sector. Consequently, income from legal activity is increasing in social capital, conditional on employment.

Social capital is cumulative and, following the approach of Becker and Murphy (1988), investment will be considered as proportional to the level of effort and other resources spent in legitimate activity. Resources in this model are represented by time. Social capital also depends on the state of the world, which is learnt at the beginning of each period. In the event of not being apprehended for crimes committed in time $t$, which occurs with probability $(1-p)$, social capital at $t+1$ is given by:

$$S_{t+1} = (1 - \delta)S_t + \gamma L_t$$

where $\delta$ is the depreciation rate of social capital and $\gamma$ transforms resources spent in legitimate activity into social capital.
With probability, $p$, the individual will be apprehended at the beginning of $t+1$ and a social sanction imposed. This sanction is represented by a loss to the individual's social capital stock. The loss will depend positively on the total amount of time devoted to crime (both income and consumption generating crime) and the level of social capital stock the individual has accumulated. In this way, we capture the feature that, *ceteris paribus*, the expected cost of crime is greater for those with a higher level of social stock than it is for people who are less tightly bonded to their community. Thus, in the event of apprehension, social capital at the beginning of $t+1$ is given by:

$$S_{t+1} = \{(1 - \delta) - \alpha C_t\}S_t$$

where $\alpha$ represents the technology that transforms resources spent in crime to social capital and

$$C_t = C^e_t + C^f.$$ 

The probability of apprehension is treated as exogenous and constant in this model. We relax this assumption in Chapter 7.

A representative individual's dynamic programming problem is characterized by his value function at period $t$, $V(A_t, S_t)$, which is the solution to the Bellman equation:

$$V(A_t, S_t) = \max_{X_t, L_t, C^e_t, C^f} U(X_t, L_t, C^e_t, S_t) + \beta \left\{ pV(A_{t+1}, S_{t+1}) + (1 - p)V(A_{t+1}, S_{t+1}^0) \right\}$$

Subject to:  
1) $T = L_t + L_t + C_t$
2) \( C_t = C_t^C + C_t^l \)

3) \( A_{t+1} = (1 + r)(A_t + W_t(L_t, S_t) + W(C^l_t - X_t) \)

4) \( S_{t+1}^l = ((1 - \delta) - \alpha C_t) S_t \) if caught
\( S_{t+1}^0 = (1 - \delta) S_t + \gamma L_t \) if not caught.

By substituting (1) in for \( \ell_t \), we eliminate \( \ell_t \) as a choice variable. The first order conditions with respect to \( X_t, L_t, C_t^C \) and \( C_t^l \) are:

\[
\frac{\partial V(A_t, S_t)}{\partial X_t} = U_1(t) - \beta (1 + r) \left\{ p \frac{\partial V(A_{t+1}, S_{t+1}^l)}{\partial A_{t+1}} + (1 - p) \frac{\partial V(A_{t+1}, S_{t+1}^0)}{\partial A_{t+1}} \right\} = 0 \tag{3.1}
\]

\[
\frac{\partial V(A_t, S_t)}{\partial A_t} = -U_2(t) + \beta \gamma (1 - p) \frac{\partial V(A_{t+1}, S_{t+1}^0)}{\partial S_{t+1}} + \beta (1 + r) \frac{\partial W(L_t, S_t)}{\partial L_t} \left\{ p \frac{\partial V(A_{t+1}, S_{t+1}^l)}{\partial A_{t+1}} + (1 - p) \frac{\partial V(A_{t+1}, S_{t+1}^0)}{\partial A_{t+1}} \right\} = 0 \tag{3.2}
\]

\[
\frac{\partial V(A_t, S_t)}{\partial C_t^C} = U_3(t) - U_2(t) - \beta \alpha S_t p \frac{\partial V(A_{t+1}, S_{t+1}^l)}{\partial S_{t+1}} = 0 \tag{3.3}
\]

\[
\frac{\partial V(A_t, S_t)}{\partial C_t^l} = -U_2(t) - \alpha \beta S_t p \frac{\partial V(A_{t+1}, S_{t+1}^l)}{\partial S_{t+1}} + \beta (1 + r) \frac{\partial W(C^l_t)}{\partial C_t^l} \left\{ p \frac{\partial V(A_{t+1}, S_{t+1}^l)}{\partial A_{t+1}} + (1 - p) \frac{\partial V(A_{t+1}, S_{t+1}^0)}{\partial A_{t+1}} \right\} = 0 \tag{3.4}
\]
The first order conditions show that in equilibrium, an individual chooses (1) current consumption so as to equate the marginal utility of current period consumption with the expected marginal loss of future welfare due to diminished assets, (2) the amount of time allocated to income producing legitimate activity so as to equate the marginal utility cost of forgone leisure to the expected marginal benefit of increased assets in future periods plus the expected increase in future welfare from the accumulation of social capital, (3) current time in consumption crime so as to equate the marginal utility of time in consumption crime to the marginal utility cost of forgone leisure plus the expected decrease in future welfare associated with being apprehended and incurring a social sanction, and (4) the amount of time allocated to income producing crime so as to equate the marginal utility cost of forgone leisure plus the expected decrease in future welfare associated with being apprehended and incurring a social sanction to the expected marginal benefit of increased assets in future periods.

We now derive the Euler equations for the social capital model of crime. To obtain the Euler equation for $X_t$, we invoke the envelope theorem to solve out for the partial derivatives of the value function. By the envelope theorem:

$$\frac{\partial V(A_t, S_t)}{\partial A_t} = \beta (1+r) \left[ p \frac{\partial V(A_{t+1}, S_{t+1})}{\partial A_{t+1}} + (1-p) \frac{\partial V(A_{t+1}, S_{t+1})}{\partial A_{t+1}} \right].$$

(3.5)

Substituting (3.1) into (3.5), we have:
\[
\frac{\partial V(A_t, S_t)}{\partial A_t} = U_1(t)
\]  \hspace{1cm} (3.6)

Updating (3.6) one period:

\[
\frac{\partial V(A_{t+1}, S_{t+1})}{\partial A_{t+1}} = U_1(t + 1)
\]  \hspace{1cm} (3.7)

Evaluating (3.7) at \(S_{t+1}^1\) and \(S_{t+1}^0\), we obtain (3.8) and (3.9) respectively.

\[
\frac{\partial V(A_{t+1}, S_{t+1}^1)}{\partial A_{t+1}} = U_1^1(t + 1)
\]  \hspace{1cm} (3.8)

\[
\frac{\partial V(A_{t+1}, S_{t+1}^0)}{\partial A_{t+1}} = U_1^0(t + 1)
\]  \hspace{1cm} (3.9)

Substituting (3.8) and (3.9) into equation (3.1), we obtain the Euler equation for \(X_t\).

\[
X_t: U_1(t) - \beta(1+r)\{pU_1^1(t + 1) + (1 - p)U_1^0(t + 1)\} = 0
\]  \hspace{1cm} (3.10)

To solve for the partial derivatives of the value function in the remaining first order conditions, we use the envelope theorem again. From the envelope theorem:

\[
\frac{\partial V(A_t, S_t)}{\partial S_t} = U_4(t) + \beta \left\{ (1 - \delta - \alpha C_t) p \frac{\partial V(A_{t+1}, S_{t+1}^1)}{\partial S_{t+1}} \right. \\
\left. + (1 - \delta)(1 - p) \frac{\partial V(A_{t+1}, S_{t+1}^0)}{\partial S_{t+1}} \right\}
\]  \hspace{1cm} (3.11)
To obtain expressions for the partial derivatives of the value function with respect to social capital in each state of the world, substitute first order condition (3.1) into (3.2) and (3.3) to obtain (3.12) and 3.13 respectively.

\[-U_2(t) + U_1(t) \frac{\partial W_c(L_t, S_t)}{\partial L_t} + \beta \gamma (1 - p) \frac{\partial V(A_{t+1}, S_{t+1}^0)}{\partial S_{t+1}} = 0\]  \hspace{1cm} (3.12)

\[-U_2(t) + U_1(t) \frac{\partial W_c(C_t)}{\partial C_t} - \beta \alpha S_t p \frac{\partial V(A_{t+1}, S_{t+1}^1)}{\partial S_{t+1}} = 0\]  \hspace{1cm} (3.13)

Substituting (3.12) and (3.13) into (3.11), we obtain:

\[\frac{\partial V(A_t, S_t)}{\partial S_t} = U_4(t) + \frac{(1 - \delta)}{\gamma} \left\{ U_2(t) + U_1(t) \frac{\partial W_c(L_t, S_t)}{\partial L_t} \right\} + \frac{(1 - \delta - \alpha C_t)}{\alpha S_{t+1}} \left\{ U_1(t) \frac{\partial W_c(C_t)}{\partial C_t} - U_2(t) \right\}\]  \hspace{1cm} (3.14)

Updating (3.14) by one period:

\[\frac{\partial V(A_{t+1}, S_{t+1})}{\partial S_{t+1}} = U_4(t + 1) + \frac{(1 - \delta)}{\gamma} \left\{ U_2(t + 1) + U_1(t + 1) \frac{\partial W_c(L_{t+1}, S_{t+1})}{\partial L_{t+1}} \right\} + \frac{(1 - \delta - \alpha C_{t+1})}{\alpha S_{t+1}} \left\{ U_1(t + 1) \frac{\partial W_c(C_{t+1})}{\partial C_{t+1}} - U_2(t + 1) \right\}\]  \hspace{1cm} (3.15)

Evaluating (3.15) at $S_{t+1}^0$ and $S_{t+1}^1$ respectively, we obtain:
\[
\frac{\partial V}{\partial S_{t+1}}(A_{t+1},S_{t+1})^0 = U_4^0(t+1) \left[ \frac{1}{\gamma} \left( U_2^0(t+1) + U_1^0(t+1) \frac{\partial W_L(L_{t+1},S_{t+1})}{\partial L_{t+1}} \right) \right] + \frac{(1-\delta) - \alpha C_{t+1}^0}{\alpha S_{t+1}^0} \left[ U_1^0(t+1) \frac{\partial W_L(L_{t+1},S_{t+1})}{\partial C_{t+1}} - U_2^0(t+1) \right] \tag{3.16}
\]

\[
\frac{\partial V}{\partial S_{t+1}}(A_{t+1},S_{t+1})^1 = U_4^1(t+1) + \frac{(1-\delta) - \alpha C_{t+1}^1}{\gamma} \left[ U_2^1(t+1) + U_1^1(t+1) \frac{\partial W_L(L_{t+1},S_{t+1})}{\partial L_{t+1}} \right] + \frac{(1-\delta) - \alpha C_{t+1}^1}{\alpha S_{t+1}^1} \left[ U_1^1(t+1) \frac{\partial W_L(L_{t+1},S_{t+1})}{\partial C_{t+1}} - U_2^1(t+1) \right] \tag{3.17}
\]

Substitute (3.16) into (3.2) and (3.17) into (3.4) to obtain the Euler equations for time in legitimate income producing activities, \(L_t\), and criminal income producing activities, \(C_t^i\):

\[
L_t: U_1(t) \frac{\partial W_L(L_t,S_t)}{\partial L_t} - U_2(t) + \beta \gamma (1-p) \left[ \frac{(1-\delta) - \alpha C_{t+1}^0}{\gamma} \right] U_2^0(t+1) + \left( \frac{\partial W_L(L_{t+1},S_{t+1})}{\partial S_{t+1}} + \frac{(1-\delta) - \alpha C_{t+1}^0}{\alpha S_{t+1}^0} \frac{\partial W_L(L_{t+1},S_{t+1})}{\partial C_{t+1}} \right) U_1^0(t+1) + U_2^0(t+1) = 0
\]

\[
C_t^i: U_1(t) \frac{\partial W_L(C_t)}{\partial C_t} - U_2(t) - \beta \rho S_t \left[ \frac{(1-\delta) - \alpha C_{t+1}^i}{\gamma} \right] U_2^i(t+1) + \left( \frac{\partial W_L(L_{t+1},S_{t+1})}{\partial S_{t+1}} + \frac{(1-\delta) - \alpha C_{t+1}^i}{\alpha S_{t+1}^i} \frac{\partial W_L(L_{t+1},S_{t+1})}{\partial C_{t+1}} \right) U_1^i(t+1) + U_2^i(t+1) = 0
\]
To obtain the Euler equation for time in consumption producing crime, $C^C_t$, substitute (3.13) into the first order condition (3.3).

$$C^C_t: U_3(t) - U_1(t) \frac{\partial W_C(C^l_t)}{\partial C^l_t} = 0$$

Our final set of Euler equations are:

$$X_t: U_1(t) - \beta(1+r)\left[p U_1^1(t+1) + (1-p) U_1^0(t+1)\right] = 0$$

$$L_t: U_1(t) \frac{\partial W_L(L_t, S_t)}{\partial L_t} - U_2(t) + \beta \gamma(1-p) \left[ \left( \frac{1-\delta}{\gamma} - \left( \frac{1-\delta - \alpha C_{t+1}^0}{\alpha S_{t+1}^0} \right) \right) U_2^0(t+1) \right.$$

$$\left. + \left( \frac{\partial W_L(L_{t+1}^0, S_{t+1}^0)}{\partial S_{t+1}^0} \right) + \left( \frac{1-\delta - \alpha C_{t+1}^0}{\alpha S_{t+1}^0} \right) \frac{\partial W_C(C_{t+1}^0)}{\partial C_{t+1}^0} \right)$$

$$\left. - \frac{(1-\delta)}{\gamma} \frac{\partial W_L(L_{t+1}^0, S_{t+1}^0)}{\partial L_{t+1}} \right] U_1^0(t+1) + U_4^0(t+1) = 0$$

$$C^C_t: U_3(t) - U_1(t) \frac{\partial W_C(C^l_t)}{\partial C^l_t} = 0$$

$$C^l_t: U_1(t) \frac{\partial W_C(C^l_t)}{\partial C^l_t} - U_2(t) - \beta \alpha p S_t \left[ \left( \frac{1-\delta}{\gamma} - \left( \frac{1-\delta - \alpha C_{t+1}^l}{\alpha S_{t+1}^l} \right) \right) U_2^l(t+1) \right.$$

$$\left. + \left( \frac{\partial W_L(L_{t+1}^l, S_{t+1}^l)}{\partial S_{t+1}^l} \right) + \left( \frac{1-\delta - \alpha C_{t+1}^l}{\alpha S_{t+1}^l} \right) \frac{\partial W_C(C_{t+1}^l)}{\partial C_{t+1}^l} \right)$$

$$\left. - \frac{(1-\delta)}{\gamma} \frac{\partial W_L(L_{t+1}^l, S_{t+1}^l)}{\partial L_{t+1}} \right] U_1^l(t+1) + U_4^l(t+1) = 0$$
Notice that the Euler equation for the aggregate consumption good gives the usual condition for optimality in consumption. The ratio of the marginal utility of current period consumption to the expected marginal utility of next period's consumption is equated to the gross real rate of interest. The Euler equation for time in consumption producing crime reflects the assumption that the legitimate community does not differentiate between the two types of crime in terms of social sanction imposed. The Euler equation for time spent in the labor market equates net current period costs associated with time at work to the expected value of the increase in social capital in terms of next period decision variables. Similarly, the Euler equation for time spent in illegitimate income generating activities equates the net marginal benefit this period to the expected future cost. Once functional forms are specified for the utility and wage functions, the Euler equations give a closed form solution for the optimal allocation of resources.
CHAPTER 4

DATA

Lack of individual level data on criminal activity from a representative population has been a major impediment to the study of crime (Cornwell and Trumbull, 1994). Witte (1980) defines the economist's ideal data set for empirically testing the economic model of crime as information on the allocation of time for a random sample of the population. She notes that the most difficult information to obtain is the time allocated to illegal activities. Much criminal activity is not reported, and of that reported, much does not lead to the arrest of the perpetrator.

The data used in this investigation is distinguished from other data used to study crime by its ability to meet Witte's criteria. The 1958 Philadelphia Birth Cohort Study (Wolfgang, Figlio, and Tracy, 1988) draws on a general urban population. Further, it contains information on both official reports and self-reports of criminal activity. These sources are combined to create annual observations on the allocation of time to criminal activity for the sample. Before discussing the construction of variables, we provide a brief description of the collection and organization of the 1958 Philadelphia Birth Cohort Study.
4.1 Description of the 1958 Philadelphia Birth Cohort Study

The 1958 Philadelphia Birth Cohort Study (Wolfgang, Figlio, and Tracy, 1988) has a universe of *all* individuals born in 1958 who lived in Philadelphia at least from their tenth until their eighteenth birthday. Public and parochial school records were used to identify the 27,160 subjects who met these criteria. The race and gender breakdown of the subjects are contained in Table 1.

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Number and Percentage of 1958 Cohort Members by Race and Sex</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sex</td>
</tr>
<tr>
<td>---------</td>
<td>-------------------</td>
</tr>
<tr>
<td>Male</td>
<td>6,216</td>
</tr>
<tr>
<td>Female</td>
<td>22.90%</td>
</tr>
<tr>
<td>6,637</td>
<td>7,363</td>
</tr>
<tr>
<td>Female</td>
<td>24.40%</td>
</tr>
<tr>
<td>Total</td>
<td>12,853</td>
</tr>
<tr>
<td>Total</td>
<td>47.30%</td>
</tr>
</tbody>
</table>

Juvenile and adult arrest records up to age 26 were collected for the cohort members. Rap sheet and police investigation reports provided by the Juvenile Aid Division of the Philadelphia Police Department were used to characterize all police encounters experienced by the cohort before age eighteen. The adult criminal justice data come from the Municipal and Common Pleas Courts of Philadelphia. These data include rap sheet information on every offense committed in Philadelphia by cohort members who were eighteen years of age or older up until December 31, 1984. Both the adult and juvenile offense data were scored by means of a system designed to index the gravity of illegal
behavior. This system, developed by Sellin and Wolfgang (1964), uses 100 separate variables from the rap sheet data for each offense. The procedure for severity scoring is discussed further in Appendix 2.

In the final stage of the Study, the cohort was stratified by gender, race, socioeconomic status, and number of juvenile offenses (no offense and no status offenses, no offenses but status offenses, 1 offense, 2-4 offenses, 5 or more offenses). A random sample was selected from each strata for a follow-up survey that was carried out in 1988. Between 30 and 40 percent of the members in each category were ultimately interviewed. Figlio (1994) reports that comparisons among the strata indicate no apparent biases due to nonparticipation.

Only males will be used in this study because the codes which link juvenile and adult offense files with the follow-up data for women are not complete. There was a 38 percent success rate in obtaining follow-up surveys for men, resulting in a sample size of 577. Each of these men were asked over 900 questions concerning issues as diverse as employment and wage history, education, marital history, family structure and peer group relationships during childhood, parental contacts with the criminal justice system, history of physical and sexual abuse, use of drugs, and criminal activity. Questions were framed by asking for the specific date (month and year) of an event, or the time period in which the event occurred.
As part of the follow-up survey, respondents were asked to report how many times during four time periods they remembered having committed the crimes enumerated by the interviewer. The four time periods are: (1) up to and including age 11 (elementary school), (2) 12 to 18 years of age (high school), (3) 19 to 24 years of age (post high school), (4) 25 to 29 years of age (recently). Although telescoping, lack of recall, and candor are all possible in retrospective studies of this type, Figlio (1994) finds no evidence of uniform telescoping bias. In this study, the self-report data covering ages nineteen to twenty-four have been utilized, corresponding to the six year sample 1977 to 1982. Of the 577 men captured by the follow-up survey, 77 were discarded due to incomplete data for employment history and wage variables. Juvenile and adult arrest records for the full sample of males in the birth cohort, along with the follow-up survey data are used to create annual observations on 500 men for the period 1977 to 1982.

4.2 Variable Creation

To implement the model developed in Chapter 3, panel data on the variables entering the Euler equations are required. Several variables are not observed directly and must be constructed. The following section explains the process of construction for these variables.

4.2.1 Social Capital

We begin with the construction of social capital. This study examines the period 1977 to 1982, corresponding to the ages 19 to 24 years. Each individual will enter the study
period with some initial level of social capital stock, $S_0$, which has been accumulated through childhood up until the end of the year 1976, the year he turns eighteen. The initial level of social capital is assumed to result from the process which generates family social capital, as discussed in Chapter 2. During the sample period, individuals accumulate social capital through their attachments to institutions such as family and work.

In constructing the initial level of social capital stock, we begin by assuming that an individual is endowed with one unit of social capital at birth. From then until he reaches eighteen, this initial endowment is either augmented or depreciated by social capital from within his family. The follow-up survey includes data on several factors which are indicative of family social capital. In particular, presence of both parents, parental arrests during the individual's childhood, number of siblings, race and socioeconomic status of the family, gang membership, number of arrests as a juvenile, and whether high school friends had contact with police convey information about family structure and attachment to youth culture. The information contained in these measures are summarized in a composite index using the method of principal components. The principal component series are constructed by taking a weighted sum of the original variables, the weights being the elements of the characteristic vectors of the covariance matrix of the original variables. Since the objective is to obtain a one dimensional representation of all the variables under consideration, only the first principal component is used. The following table defines the variables used in the construction of $S_0$ and the corresponding weight.
Table 2
Construction of the Initial Stock of Social Capital

<table>
<thead>
<tr>
<th>Variable</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>father present in childhood home</td>
<td>0.15</td>
</tr>
<tr>
<td>father not arrested during childhood</td>
<td>0.07</td>
</tr>
<tr>
<td>number of siblings</td>
<td>-0.04</td>
</tr>
<tr>
<td>race is white</td>
<td>0.25</td>
</tr>
<tr>
<td>socioeconomic-economic status is high</td>
<td>0.29</td>
</tr>
<tr>
<td>not a gang member</td>
<td>0.28</td>
</tr>
<tr>
<td>proportion of best 3 friends from high school not picked up by the police</td>
<td>0.18</td>
</tr>
<tr>
<td>proportion of police contacts as a juvenile that result in arrest</td>
<td>-0.18</td>
</tr>
</tbody>
</table>

Notice that the weights are signed as expected. Coming from a white two parent household with a high socioeconomic status and having a father with no arrests during the individual's childhood contributes to social capital acquired from the family. Our results also indicate that not being involved in a (deviant) youth culture, such as a gang, and having friends who were not in trouble with the police facilitates the accumulation of social capital from the family. Social control theory predicts that the presence of siblings dilutes parental attention, which negatively affects a child's accumulation of social capital from his family. This prediction is also supported by the results in Table 2. Finally, we find that criminal activity, as measured by juvenile arrests, depreciates social capital acquired from the family.

Having obtained each individual's initial level of social capital, subsequent periods stock are constructed. Social capital is built through participation in legitimate activities (if not
apprehended for criminal activity) and destroyed when caught engaging in illegitimate activities. Interpreting legitimate activities in the spirit of informal social control theory implies that resources spent in building attachments to institutions such as family and community as well as work builds social capital. The data do not contain insight into the level of involvement these individuals have in their community but it does contain information about what Sampson and Laub (1993) would consider turning points, such as marriage and beginning a new job. Strong marital ties form social capital through a process of the reciprocal investment between husbands and wives. This investment creates an interdependent system of obligation and restraint which increases an individual’s bonds to society. Also, young males tend to have high job turnover rates. Assuming that leaving a job and starting a new one in the same period is attributable to upward employment mobility, a job turnover increases an individual’s attachment to the legitimate sector. The employer’s act of investing in the individual will be reciprocated by the individual. Additionally, the improvement in job increases the individual’s system of networks. These forces act together to increase his ties to the legitimate community and thus increase his social capital.

Including job turnover and beginning a marriage in the evolution of social capital, results in the following specification:

\[
S_{t+1}^1 = \left\{ (1-\delta) - \alpha C_t \right\} S_t \quad \text{if caught}
\]

\[
S_{t+1}^0 = (1-\delta) S_t + \gamma_1 L_t + \gamma_2 M_t + \gamma_3 J_t \quad \text{if not caught}
\]
where \( M_t = 1 \) if marriage began in period \( t \)
\[= 0 \text{ otherwise} \]
\( J_t = 1 \) if changed job in period \( t \)
\[= 0 \text{ otherwise} \]

To construct social capital, we require an estimate of the parameters in the social capital stock accumulation equations. We obtain these parameters by iterative application of principal components. Principal component analysis requires variables to be of a similar scale. However, the average number of hours spent at work or in crime per year are orders of magnitude larger than the index of initial social capital stock and categorical variables. Therefore, we rescale the initial level of capital stock and dummy variables by multiplying them by the number of hours in a year to be allocated by the individual.

We perform principal component analysis on (re-scaled) initial period data, including the initial level of social capital, \( S_0 = S_{77} \), to obtain a set of parameter estimates. We use observations on those arrested in 1977 in estimating the stock accumulation equation in the event of being caught. Symmetrically, observations on individuals not arrested in 1977 are used to form principal component estimates of the stock accumulation equation in the event of not being caught. We then use these parameter estimates, the 1977 level of social capital, \( S_{77} \), and data on the other variables to construct the next period's social capital, \( \hat{S}_{78} \). The equations were then (separately) re-estimated using data for 1977, 1978 and \( S_{77} \) and \( S_{78} \). This iterative procedure was followed until the full set of observations on social
capital were used in the principal components analysis. The final set of weights, shown in the table below, were then used to construct the social capital series.

Table 3

<table>
<thead>
<tr>
<th>Variable</th>
<th>Weight</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not Arrested</td>
<td></td>
<td></td>
</tr>
<tr>
<td>social capital</td>
<td>0.97</td>
<td>9675.70</td>
</tr>
<tr>
<td>time in legitimate income producing activities</td>
<td>0.08</td>
<td>1365.83</td>
</tr>
<tr>
<td>begin marriage</td>
<td>0.07</td>
<td>541.53</td>
</tr>
<tr>
<td>leave a job and start a new one</td>
<td>0.26</td>
<td>288.99</td>
</tr>
<tr>
<td>Arrested</td>
<td></td>
<td></td>
</tr>
<tr>
<td>social capital</td>
<td>0.97</td>
<td>8596.94</td>
</tr>
<tr>
<td>time in crime x social capital</td>
<td>-0.00021</td>
<td>994516.91</td>
</tr>
</tbody>
</table>

These results imply a rate of depreciation on social capital of 3% a year. If apprehended, and assuming the average time spent in crime (for those arrested) of 129 hours per year, the penalty is a further loss of 3% of social capital. Time spent in employment, getting married, and changing jobs all have a positive impact on social capital, as expected.

4.2.2 Time in Consumption and Income Producing Crime, and Income from Crime

Rap sheet data provides a systematically biased sample of crimes actually committed. Therefore, arrests are a poor measure of an individual's level of criminal involvement. In addition to official data, the Cohort Study contains self-reports on crime. Since this information is based on age categories, it cannot be directly used to infer the number of crimes committed in any given year. However, by using both official and self-report
records, we create annual observations on consumption and income crimes\(^7\) for each
member of our sample.

To create annual observations on the number of crimes from the time aggregated self-
report data, we must 'distribute' the self-reported crimes across the 6 years spanned by the
age category 19 to 24. This requires assumptions about both participation and frequency
of offending during this time period. Figlio's (1994) analysis of the self-report for males in
the follow-up survey found that the percentage of individuals committing offenses was
constant between the 19-24 and 25+ age groups when all offense types were considered.
On this basis, we make the assumption that there is a constant participation in crime
during the years 1977-1982. If the participation rate is constant, then the age-crime
profile (total number of arrests/population) for this cohort should reflect the intensity (or
frequency) with which participants commit crimes. We convert the self-reported crimes to
annual observations using the weights derived from the aggregate age-crime profile for the

The self-report data are grouped to obtain offenses corresponding to income producing
crimes and consumption crimes. To use as much of the information in the sample as
possible, consumption crimes are divided into four types: injury crimes (crimes against
another person), drug related crimes, drinking related crimes, and a residual category

\(^7\) Income producing crimes are defined to be any crimes that produce income, such as larceny, theft and
burglary, whereas consumption crimes are defined to be crimes which produce no income, such as rape,
drunk driving and hiring a prostitute.
"other". Official arrest records for the males in the cohort are similarly classified and the requisite weights generated from aggregate age-crime profiles for each crime category. The weights are then used to distribute the self-reported crimes across the six-year period. For each year and crime type, the number of crimes is defined to be the maximum of the number of self-reports and arrests. If the number of self-reported crimes is greater than the number of arrests, the total number of crimes is equal to the number of self-reports. If, however, the number of arrests is greater than the number of self-reports, the number of crimes is set equal to the number of arrests. This latter case is only relevant for individuals who have an arrest record. The number of self-reports falls short of the number of arrests in 6.4 percent of the consumption crime observations, and 8.5 percent of the income crime observations, on criminals.

Having obtained a measure of the number of crimes committed in a year, we convert the quantity of crimes into time in crime. This requires a basis for comparison and aggregation across the different crime types. Wolfgang and Sellin (1964) propose a seriousness scoring scale which uses the effects of the crimes rather than specific legal labels to index the gravity of criminal behavior. The index of severity serves as a metric for comparison and aggregation of different crimes. To score a crime, detailed information is required (see Appendix 2, on the seriousness scoring system). This data was collected from the rap sheets on arrests and seriousness scores calculated. However, the information is unknown for crimes for which no arrests take place. In this case, seriousness scores must be generated. We do this by taking random draws from the
distribution of seriousness scores for arrests in the corresponding crime category.

Similarly, there are no self-report data on income from crime. Consequently, these data must be generated by taking random draws from the distribution of income from crime that was obtained from rap sheet data. Annual observations on income from crime and seriousness scores for consumption crime and income generating crime are obtained by aggregating across the respective variables within a year.

Inspection of the resulting seriousness scores revealed a range for total crime (consumption plus income) an order of magnitude smaller than the number of hours spent at work in a year. We therefore convert seriousness scores to hours by scaling up by a factor of ten.

4.2.3 Time in Legitimate Income Producing Activities and Legitimate Income

The follow-up survey contains detailed information on employment histories for 500 males in the study. In particular, for each job (whose tenure was at least six months), wage income when the individual began and ended employment, whether the job was part time or full time, the pay period (hourly, weekly, monthly, or yearly), and the average hours worked per week, were recorded. This information was augmented by information about service in the armed forces, which was included as non-work histories. The employment and armed forces service histories were used to construct annual observations on the number of hours worked per year and annual labor income from legitimate labor market activities.
Having obtained empirical measures of key variables, we are now ready to implement the model developed in Chapter 3. Before imposing this mathematical structure, however, we pause to take a more heuristic look at the data. The following chapter examines whether data from the 1958 Philadelphia Birth Cohort Study are generally consistent with our integrated approach to crime.
CHAPTER 5

DATA VERSUS MODEL: EVIDENCE FOR AN INTEGRATED APPROACH TO CRIME

This chapter discusses characteristics of the data, as they relate to the predictions of our dynamic model of crime. Recall the motivation for a dynamic framework. First, it allows us to formulate a theory of rational criminal choice, where agents anticipate the future consequences of their decisions. In our model, current period decisions affect future decisions through the process of social capital accumulation. Social capital is a measure of the attachment an individual has to legitimate society. The model predicts that people who are more attached to the labor force and have a cohesive marriage are less likely to engage in crime. Further, it suggests that characteristics of an individual's family background, such as presence of both parents, and gang affiliation, may affect adult earnings (through intergenerational transmission of human capital) and criminal activity (through transmission of norms). The second reason for moving to a dynamic setting is the empirical regularity of the age-crime profile. Our model seeks to explain this phenomenon through the process of social capital accumulation. Social control theory posits that as an individual ages, his ties to legitimate society strengthen. These social ties create interdependent systems of obligation and restraint that impose significant costs for translating criminal propensities into crime, making the occurrence of crime less likely. The means by which an individual becomes more closely bonded to society is represented in our formulation by the individual building social capital. We begin by providing
evidence on the dynamic nature of criminal behavior for the individuals of the 1958 Philadelphia Birth Cohort.

5.1 Evidence of the Dynamic Nature of Crime

One compelling motivation for a dynamic model of crime is that a static approach cannot explain the empirical regularity called the age-crime profile. The age-crime profile describes the age distribution of the aggregate arrest rate. In studies of different countries, cities, and across different periods of time, the aggregate arrest rate is found to be a unimodal positively skewed function of age. Figure 1 shows that the age-crime profile for males born in Philadelphia in 1958 also displays this temporal pattern.

Figure 1.
Age Crime Profile for the Philadelphia Birth Cohort

AGE CRIME PROFILE
(all crimes)

ARREST RATE

AGE

18 19 20 21 22 23 24 25 26
In our model, crime is decomposed into consumption and income generating crimes.

Figure 2 demonstrates that the age-crime profile based on the 1958 Philadelphia Cohort is not sensitive to this distinction.

![Age Crime Profile by Crime Type for the Philadelphia Birth Cohort](image)

The negative correlation between the arrest rate and age transcends geography and time. It cannot be explained by culture or government policy on incapacitation and deterrence. Rather, its explanation must lie in events which occur over the life-cycle. The hypothesis put forward in our formulation is that as an individual ages, he marries and settles into a career path. In doing so, he strengthens his ties to the legitimate community. These social ties are important in that they create interdependent systems of obligation and restraint that impose significant costs for translating criminal propensities into crime, making the occurrence of crime less likely.
5.2 Evidence In Support of an Integrated Approach to Crime

Having established the dynamic nature of the decision to participate in crime, we now investigate the relative merits of human and social capital theory using the follow-up sample from the 1958 Philadelphia Cohort Study.

According to the human capital approach, legitimate market wages are an increasing function of human capital. Therefore, individuals with low levels of human capital receive low market wages. Since they face a lower opportunity cost of forgone earnings (relative to those individuals with more human capital) these individuals are less likely to participate in the labor market and more likely to commit crime. Table 4 shows that, for the members of this sample, human capital does determine earnings. (Note that these individuals turn 18 during 1976). However, conditional on working, criminals and noncriminals do not appear to differ in their earnings ability.

Table 4
Average Annual Income by Level of Education and Criminal Status

<table>
<thead>
<tr>
<th>Year</th>
<th>No High School Diploma</th>
<th>High School Graduate</th>
<th>College Graduate</th>
<th>Criminal</th>
<th>Noncriminal</th>
</tr>
</thead>
<tbody>
<tr>
<td>76</td>
<td>6,344</td>
<td>4,990</td>
<td>2,802</td>
<td>5,370</td>
<td>5,585</td>
</tr>
<tr>
<td>77</td>
<td>8,381</td>
<td>7,957</td>
<td>5,848</td>
<td>7,931</td>
<td>8,146</td>
</tr>
<tr>
<td>78</td>
<td>9,287</td>
<td>10,298</td>
<td>5,313</td>
<td>10,270</td>
<td>9,546</td>
</tr>
<tr>
<td>79</td>
<td>10,633</td>
<td>11,604</td>
<td>6,263</td>
<td>11,583</td>
<td>10,869</td>
</tr>
<tr>
<td>80</td>
<td>11,144</td>
<td>13,009</td>
<td>7,167</td>
<td>12,454</td>
<td>11,834</td>
</tr>
<tr>
<td>81</td>
<td>12,424</td>
<td>13,505</td>
<td>11,240</td>
<td>12,724</td>
<td>13,063</td>
</tr>
<tr>
<td>82</td>
<td>12,873</td>
<td>14,189</td>
<td>16,594</td>
<td>13,922</td>
<td>14,029</td>
</tr>
<tr>
<td>83</td>
<td>14,059</td>
<td>15,227</td>
<td>20,037</td>
<td>15,147</td>
<td>15,374</td>
</tr>
<tr>
<td>84</td>
<td>14,579</td>
<td>15,890</td>
<td>20,852</td>
<td>15,105</td>
<td>16,408</td>
</tr>
</tbody>
</table>
Annual labor income depends on the number of hours worked in a year and the hourly wage. In Table 5, we attempt to decouple these effects by considering the hourly wage rate. Once again, we find that human capital determines earnings and, conditional on working, criminals and noncriminals do not appear to differ in the hourly wage rates they receive. If anything, criminals appear to attract a slightly higher wage rate. This is inconsistent with the notion that individuals engage in crime because they face a lower opportunity cost of forgone earnings than noncriminals.

<table>
<thead>
<tr>
<th>Year</th>
<th>No High School Diploma</th>
<th>High School Graduate</th>
<th>College Graduate</th>
<th>Criminal</th>
<th>Noncriminal</th>
</tr>
</thead>
<tbody>
<tr>
<td>76</td>
<td>4.46</td>
<td>4.23</td>
<td>2.93</td>
<td>4.56</td>
<td>4.11</td>
</tr>
<tr>
<td>77</td>
<td>4.82</td>
<td>4.70</td>
<td>4.4</td>
<td>4.95</td>
<td>4.59</td>
</tr>
<tr>
<td>78</td>
<td>5.24</td>
<td>5.34</td>
<td>4.48</td>
<td>5.54</td>
<td>5.13</td>
</tr>
<tr>
<td>79</td>
<td>5.53</td>
<td>5.78</td>
<td>4.62</td>
<td>5.92</td>
<td>5.53</td>
</tr>
<tr>
<td>80</td>
<td>6.09</td>
<td>6.3</td>
<td>5.68</td>
<td>6.33</td>
<td>6.13</td>
</tr>
<tr>
<td>81</td>
<td>6.51</td>
<td>6.59</td>
<td>6.69</td>
<td>6.63</td>
<td>6.54</td>
</tr>
<tr>
<td>82</td>
<td>6.58</td>
<td>6.87</td>
<td>7.78</td>
<td>6.88</td>
<td>6.86</td>
</tr>
<tr>
<td>83</td>
<td>6.90</td>
<td>7.33</td>
<td>8.91</td>
<td>7.39</td>
<td>7.31</td>
</tr>
<tr>
<td>84</td>
<td>7.09</td>
<td>7.67</td>
<td>9.40</td>
<td>7.55</td>
<td>7.70</td>
</tr>
</tbody>
</table>
Interestingly, the data also indicate no 'scarring' effects on earnings (for those employed) from arrests as a minor, as shown in Table 6.

<table>
<thead>
<tr>
<th>Year</th>
<th>Total</th>
<th>Juvenile Delinquent</th>
<th>Nondelinquent Delinquent</th>
</tr>
</thead>
<tbody>
<tr>
<td>76</td>
<td>5,499</td>
<td>5,525</td>
<td>5,442</td>
</tr>
<tr>
<td>77</td>
<td>8,060</td>
<td>8,448</td>
<td>7,288</td>
</tr>
<tr>
<td>78</td>
<td>9,821</td>
<td>10,414</td>
<td>8,782</td>
</tr>
<tr>
<td>79</td>
<td>11,128</td>
<td>11,859</td>
<td>9,868</td>
</tr>
<tr>
<td>80</td>
<td>12,044</td>
<td>12,761</td>
<td>10,908</td>
</tr>
<tr>
<td>81</td>
<td>12,945</td>
<td>13,455</td>
<td>12,165</td>
</tr>
<tr>
<td>82</td>
<td>13,992</td>
<td>14,018</td>
<td>13,951</td>
</tr>
<tr>
<td>83</td>
<td>15,295</td>
<td>15,224</td>
<td>15,406</td>
</tr>
<tr>
<td>84</td>
<td>15,945</td>
<td>16,030</td>
<td>15,813</td>
</tr>
</tbody>
</table>

While explaining the relationship between education and earnings, the model of human capital appears to offer little insight into the decision to participate in crime by the members of this sample.

The basic premise of the social capital approach is that crime is more likely for those who are weakly attached to society. One of the most important institutions through which social capital is formed is employment. Therefore, social capital theory predicts that people who are more attached to the labor force are less likely to engage in crime. Table 7 provides evidence in support of this prediction. Criminals have a lower employment rate relative to noncriminals in the sample (despite the fact that criminals who work earn similar incomes to noncriminals). Notice also that social capital as a theory of
crime is in no way in conflict with human capital as a theory of labor market behavior. Agents with a larger stock of human capital have a higher participation rate than those with a smaller stock.

Table 7

*Employment Rate by Level of Education and Criminal Status*

<table>
<thead>
<tr>
<th>Year</th>
<th>Did Not Graduate High School</th>
<th>High School Graduate</th>
<th>College Graduate</th>
<th>Criminal</th>
<th>Noncriminal</th>
</tr>
</thead>
<tbody>
<tr>
<td>76</td>
<td>0.52</td>
<td>0.46</td>
<td>0.15</td>
<td>0.46</td>
<td>0.45</td>
</tr>
<tr>
<td>77</td>
<td>0.62</td>
<td>0.70</td>
<td>0.2</td>
<td>0.64</td>
<td>0.62</td>
</tr>
<tr>
<td>78</td>
<td>0.64</td>
<td>0.78</td>
<td>0.22</td>
<td>0.66</td>
<td>0.70</td>
</tr>
<tr>
<td>79</td>
<td>0.64</td>
<td>0.84</td>
<td>0.27</td>
<td>0.66</td>
<td>0.75</td>
</tr>
<tr>
<td>80</td>
<td>0.63</td>
<td>0.85</td>
<td>0.49</td>
<td>0.64</td>
<td>0.79</td>
</tr>
<tr>
<td>81</td>
<td>0.66</td>
<td>0.84</td>
<td>0.78</td>
<td>0.68</td>
<td>0.82</td>
</tr>
<tr>
<td>82</td>
<td>0.69</td>
<td>0.86</td>
<td>0.90</td>
<td>0.72</td>
<td>0.85</td>
</tr>
<tr>
<td>83</td>
<td>0.70</td>
<td>0.85</td>
<td>0.93</td>
<td>0.72</td>
<td>0.85</td>
</tr>
<tr>
<td>84</td>
<td>0.71</td>
<td>0.86</td>
<td>0.98</td>
<td>0.75</td>
<td>0.86</td>
</tr>
</tbody>
</table>

As further evidence in favor of social capital theory, consider the role of family social capital in the transmission of norms such as work ethic and nondeviant behavior. Recall that two of the most important factors that cause a lack of family social capital are the absence of a parent and the child's embeddedness in a youth community, such as a gang. Table 8 shows employment rates by presence of father and gang membership. Not having a father present during childhood and gang membership clearly have a strong and sustained negative impact on the labor force attachment of the men in this sample.
Table 8

Employment Rate by Characteristics of Childhood

<table>
<thead>
<tr>
<th>Year</th>
<th>Father Present</th>
<th>Father Not Present</th>
<th>Gang Member</th>
<th>Not a Gang Member</th>
</tr>
</thead>
<tbody>
<tr>
<td>76</td>
<td>0.46</td>
<td>0.44</td>
<td>0.44</td>
<td>0.46</td>
</tr>
<tr>
<td>77</td>
<td>0.64</td>
<td>0.60</td>
<td>0.64</td>
<td>0.63</td>
</tr>
<tr>
<td>78</td>
<td>0.69</td>
<td>0.65</td>
<td>0.74</td>
<td>0.66</td>
</tr>
<tr>
<td>79</td>
<td>0.73</td>
<td>0.64</td>
<td>0.74</td>
<td>0.71</td>
</tr>
<tr>
<td>80</td>
<td>0.75</td>
<td>0.65</td>
<td>0.72</td>
<td>0.74</td>
</tr>
<tr>
<td>81</td>
<td>0.79</td>
<td>0.67</td>
<td>0.74</td>
<td>0.78</td>
</tr>
<tr>
<td>82</td>
<td>0.82</td>
<td>0.71</td>
<td>0.76</td>
<td>0.82</td>
</tr>
<tr>
<td>83</td>
<td>0.83</td>
<td>0.69</td>
<td>0.76</td>
<td>0.82</td>
</tr>
<tr>
<td>84</td>
<td>0.84</td>
<td>0.73</td>
<td>0.77</td>
<td>0.83</td>
</tr>
</tbody>
</table>

Similar effects result from parental arrests and delinquent behavior, as shown in Table 9. It seems that a parent's involvement in crime has a larger impact on the transmission of legitimate norms than a child's involvement in crime. It is also interesting that the effects of a lack of family social capital, reflected by an individual's involvement in juvenile crime, can affect him into adulthood.

Table 9

Employment Rate by Characteristics of Childhood

<table>
<thead>
<tr>
<th>Year</th>
<th>Father Arrested</th>
<th>Father Not Arrested</th>
<th>Juvenile Delinquent</th>
<th>Nondelinquent</th>
</tr>
</thead>
<tbody>
<tr>
<td>76</td>
<td>0.45</td>
<td>0.46</td>
<td>0.50</td>
<td>0.38</td>
</tr>
<tr>
<td>77</td>
<td>0.65</td>
<td>0.63</td>
<td>0.66</td>
<td>0.58</td>
</tr>
<tr>
<td>78</td>
<td>0.75</td>
<td>0.68</td>
<td>0.68</td>
<td>0.68</td>
</tr>
<tr>
<td>79</td>
<td>0.69</td>
<td>0.72</td>
<td>0.72</td>
<td>0.72</td>
</tr>
<tr>
<td>80</td>
<td>0.64</td>
<td>0.75</td>
<td>0.73</td>
<td>0.75</td>
</tr>
<tr>
<td>81</td>
<td>0.67</td>
<td>0.78</td>
<td>0.75</td>
<td>0.80</td>
</tr>
<tr>
<td>82</td>
<td>0.71</td>
<td>0.81</td>
<td>0.78</td>
<td>0.83</td>
</tr>
<tr>
<td>83</td>
<td>0.69</td>
<td>0.82</td>
<td>0.79</td>
<td>0.83</td>
</tr>
<tr>
<td>84</td>
<td>0.69</td>
<td>0.83</td>
<td>0.80</td>
<td>0.85</td>
</tr>
</tbody>
</table>
Although delinquent status does not impact adult wages, conditional on working, those who were juvenile delinquents have a weaker attachment to the labor market as adults.

Notably, the data provide evidence of the importance of family social capital in the transmission of human capital, as shown in Table 10. Annual incomes are consistently higher for men who had their father living with them during childhood compared to those whose fathers were absent. Similarly, men who were in a gang in their youth are found to earn less through adulthood compared to those who were not.

<table>
<thead>
<tr>
<th>Year</th>
<th>Gang Member</th>
<th>Not a Gang Member</th>
<th>Father Present</th>
<th>Father Not Present</th>
</tr>
</thead>
<tbody>
<tr>
<td>76</td>
<td>4,711</td>
<td>5,758</td>
<td>5,609</td>
<td>4,981</td>
</tr>
<tr>
<td>77</td>
<td>7,195</td>
<td>8,371</td>
<td>8,354</td>
<td>6,743</td>
</tr>
<tr>
<td>78</td>
<td>8,810</td>
<td>10,231</td>
<td>10,054</td>
<td>8,770</td>
</tr>
<tr>
<td>79</td>
<td>10,910</td>
<td>11,212</td>
<td>11,337</td>
<td>10,123</td>
</tr>
<tr>
<td>80</td>
<td>11,539</td>
<td>12,214</td>
<td>12,299</td>
<td>10,798</td>
</tr>
<tr>
<td>81</td>
<td>11,647</td>
<td>13,369</td>
<td>13,339</td>
<td>11,045</td>
</tr>
<tr>
<td>82</td>
<td>12,818</td>
<td>14,384</td>
<td>14,584</td>
<td>11,218</td>
</tr>
<tr>
<td>83</td>
<td>14,080</td>
<td>15,700</td>
<td>15,837</td>
<td>12,718</td>
</tr>
<tr>
<td>84</td>
<td>14,033</td>
<td>16,596</td>
<td>16,544</td>
<td>13,220</td>
</tr>
</tbody>
</table>

5.3 Further Evidence in Support of an Integrated approach

In this section we investigate the influence of factors which affect social capital formation in childhood on adult criminality. In particular, we consider family structure, father’s
criminality, gang membership, and involvement in juvenile crime on the probability of criminal behavior in adulthood.

Table 11 contains the results of estimation for 5 bivariate probit models. In each case the latent dependent variable is the probability of becoming a criminal. Individuals are considered criminals if they have been arrested at least once during the period 1976-1984.

<table>
<thead>
<tr>
<th>Variable^b</th>
<th>Coefficient</th>
<th>Slope</th>
<th>Pr(Criminal) X=1</th>
<th>Pr(Criminal) X=0</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARCON</td>
<td>0.607</td>
<td>0.228</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(10.639)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GANGLT18</td>
<td>0.540</td>
<td>0.203</td>
<td>0.52</td>
<td>0.31</td>
</tr>
<tr>
<td></td>
<td>(8.852)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DADARREST</td>
<td>0.166</td>
<td>0.063</td>
<td>0.43</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td>(1.900)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NODAD</td>
<td>0.174</td>
<td>0.065</td>
<td>0.43</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td>(2.447)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SOCIAL CAPITAL</td>
<td>-0.018</td>
<td>-0.007</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-12.076)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

^a Figures in parentheses are t-ratios.
^b The definition of variables is given in Appendix 3.

The first probit model we consider relates the probability of criminality in adulthood to the proportion of police contacts as a juvenile that result in an arrest (ARCON). Our results confirm that for this sample of 500 men, the more involved an individual is in crime as a juvenile, the more likely he is to engage in crime as an adult. Our second probit model
relates gang involvement to participation in crime as an adult. The results in Table 11 indicate that an individual who was in a gang as a juvenile (GANGLT18) has a 52% chance of participating in crime as an adult, compared to 31% if he was not in a gang. Having no father in the household and having a father who was arrested while growing up have an identical affect on the likelihood of adult criminal behavior for our sample. Having no father when growing up increases the probability of criminality to 43% compared to 36% for those who did have a father. Similarly, an individual whose father was arrested is 20% more likely to become a criminal himself. The final row of Table 11 reports the results for the probit model relating adult criminality to our measure of initial period social capital. Recall from Chapter 4, this variable is constructed as a weighted combination of father’s presence, father’s arrests during the individual’s childhood, number of siblings, race and socioeconomic status of the family, gang membership, number of arrests as a juvenile, and whether high school friends had contact with police. Our results confirm that criminality is inversely related to our measure of initial period social capital. If we partition our sample into quartiles corresponding to their initial level of social capital, we find that men from the first quartile are more than twice as likely to become criminals compared to people from the fourth quartile. The probabilities are 52% and 24% respectively.

5.4 Summary

A necessary condition for entertaining a theory of crime is that has empirical support. As discussed in Chapter 2, there is a growing literature that casts doubt on the explanation of
crime provided by the human capital approach. We add to this literature. While human capital is found to determine earnings of men in our sample, the decision to participate in illegitimate activities cannot be explained by human capital. We do, however, find support for the theory of social capital. Factors determining family social capital are found to have a marked and sustained effect on labor market performance through adulthood, both in terms of participation and wages. We find noncriminals have a higher employment rate than criminals, which is consistent with the predictions of social capital theory. This occurs despite the fact that criminal status has no impact on adult wages, conditional on employment. Also, circumstances that are associated with a lack of family social capital, such as not having a father present in the childhood home and gang membership, have a strong negative impact on labor force attachment for this sample of men. As predicted by social control theory, their lack of social ties manifests itself in a greater likelihood of adult criminal behavior. We find an inverse relationship between our composite index of social capital and criminality. Partitioning our sample into quartiles based on their initial level of social capital, we find that men from the first quartile are more than twice as likely to be arrested during the sample period than men from the fourth quartile.
CHAPTER 6

ESTIMATION

The structural model developed in Chapter 3 characterizes the behavior of a representative individual by a system of five equations. Three of these equations are Euler equations; two describing how time is allocated across legitimate and criminal income producing activities, while the third characterizes the intertemporal consumption decision. The system also includes an earnings equation for each of the income producing activities, crime and work. These earnings equations do not depend on parameters from the utility function, nor do they depend on decisions made in (potentially unobserved) future periods. While it is possible to estimate all five equations simultaneously, the absence of unobserved future states in the earnings equations makes a sequential estimation process computationally convenient. We begin by estimating the parameters in the earnings equations. The Euler equations are then estimated in a second step using Simulated Method of Moments (McFadden and Ruud, 1994; McFadden, 1989; Pakes and Pollard, 1989) and taking the earnings equation parameters as given.

The structure of the rest of this chapter follows along the lines of our sequential estimation process. We treat the earnings and Euler equations separately and sequentially. In dealing with each, we first introduce and parameterize the model to be estimated. We then
discuss the econometric theory behind our estimation strategy and finally present the results of this estimation.

6.1 The Earnings Equations

6.1.1 The Model

Recall from Chapter 3 that an individual's income from legitimate activity, \( W_L(L_t, S_t) \), and illegitimate activity \( W_C(C_t) \) are assumed to be increasing in their respective arguments, so that:

\[
\frac{\partial W_L(L_t, S_t)}{\partial L_t} > 0, \quad \frac{\partial W_L(L_t, S_t)}{\partial S_t} > 0, \quad \frac{\partial W_L(L_t, S_t)}{\partial L_t} > 0, \quad \frac{\partial W_L(0, S_t)}{\partial L_t} = 0, \quad \frac{\partial W_C(C_t)}{\partial C_t} > 0
\]

Consistent with these assumptions, we adopt the following functional form for an individual's earnings in the legitimate sector:

\[
W_L(L_t, S_t) = \eta_0 + \eta_1 L_t + \eta_2 L_t^2 + \eta_3 L_t S_t + \eta_4 E_D + \eta_5 L_t E_D + \eta_6 S C H_t + \epsilon_{L_t}. \tag{6.1}
\]

Illegitimate earnings are parameterized as:

\[
W_C(C_t) = \mu_0 + \mu_1 C_t + \mu_2 C_t^2 + \epsilon_{C_t} \tag{6.2}
\]

where \( L_t \) and \( C_t \) denote hours per year in legitimate and criminal income generating activities respectively, \( S_t \) is the social capital stock accumulated by the individual at the beginning of period \( t \), \( E_D \) is a categorical variable equal to one if the highest level of education the individual attains is at least a high school diploma and equal to zero.
otherwise, $SCH_i$ is a categorical variable equal to one if the individual has not yet completed his education and zero otherwise and $\epsilon_L$ and $\epsilon_T$ are random error terms.

We wish to use these equations to make statements regarding the determinants of income for the entire sample of men. Since hours worked in each sector are endogenous, ordinary least squares on these equations would produce biased and inconsistent parameter estimates. This problem could be overcome through the use of an instrumental variables procedure. However, another issue to be considered in estimation is that only a subsample of the population are engaged in (either or both of) the income producing activities (recall these are young men, aged 19-24). Consequently, the time allocation variables, $L_t$ and $C_t$, are censored from below at zero hours. If the decision to work (in legitimate or illegitimate activities) depends on unobservable characteristics which also influence earnings, then the classic problem of sample selection exists. Failure to account for the affect of unobservable characteristics of the working population will lead to incorrect inference regarding the impact of observables on income. This is called sample selection bias. Since we are estimating the earnings equations separately from the Euler equations, we are able to make use of standard econometric techniques to account for the possibility of sample selection bias.

6.1.2 Estimation Theory and Method

We present the strategy used to estimate the earnings equations for both legitimate and criminal activity using a general sample selection framework. Since actual hours worked
(in either activity) is observed, we adopt the approach suggested in Vella (1993). This is a
two step method, similar to that of Heckman (1976, 1979). It differs only in that we relax
some distributional assumptions, which leads us to approximate, rather than estimate, the
selection correction term.

We begin by introducing the sample selection model. Exploiting the fact that sample
selection is a special case of a model with a censored endogenous regressor, we formulate
the problem in the following way:

\[ W_i^* = X_i \beta + \theta H_i + \varepsilon_i \quad i = 1, \ldots, n \]  \hspace{1cm} (6.3)

\[ H_i^* = Z_i \gamma + \nu_i \quad i = 1, \ldots, N \]  \hspace{1cm} (6.4)

\[ H_i = H_i^* \text{ if } H_i^* > 0; \quad H_i = 0 \text{ otherwise} \]  \hspace{1cm} (6.5)

The primary equation of interest is Equation 6.3. Equation 6.4 is the reduced form for the
latent variable (desired hours of work) and Equation 6.5 is the sample selection rule; \( X_i \)
and \( Z_i \) are exogenous variables; \( (\beta, \theta, \gamma) \) are vectors of unknown parameters; \( \varepsilon_i \) and \( \nu_i \) are
zero mean error terms with \( E[\varepsilon_i | \nu_i] = 0 \). We let \( N \) denote the sample size and \( n \) be the
subsample satisfying \( H_i > 0 \). The primary aim is to consistently estimate the parameters in
Equation 6.3, \( (\beta, \theta) \). The problem of sample selection is revealed when we take
expectations of Equation 6.3.

\[ E[ W_i | Z_i, H_i > 0] = X_i \beta + \theta H_i + E[\varepsilon_i | Z_i, H_i > 0] \]

\[ = X_i \beta + \theta H_i + E[\varepsilon_i | \nu_i] \]  \hspace{1cm} (6.6)
Since $E[\varepsilon_i|Z_i, H_i > 0] = E[\varepsilon_i|\nu_i] \neq 0$, OLS over the subsample, $n$, leads to biased and inconsistent parameter estimates.

This problem can be resolved by making assumptions about the joint distribution of the error terms $\varepsilon_i$ and $\nu_i$ then estimating the model directly by maximum likelihood. The popular Heckman two-step procedure treats the selection term, $E[\varepsilon_i|\nu_i]$ as an omitted regressor. By assuming joint normality, the correlation between the error terms is fully parameterized and is a linear function of the generalized residual from the probit (selection) model (Vella, 1996). The Heckman procedure is to first estimate the selection equation by probit over the sample of $N$ observations. In the second step, the correlation in error terms is accounted for by including the generalized residuals from the first step in Equation 6.3 and estimating over the subsample reporting $H_i > 0$ using OLS. Rather than assuming joint normality, we make the following assumptions regarding the random error terms $\varepsilon_i$ and $\nu_i$:

$\nu_i \sim iid \ N(0, \sigma^2)$

$E[\nu_i|Z_i] = 0$ and $E[\varepsilon_i|\nu_i] = f(\nu_i) \neq 0$

where $f(.)$ represents some unknown function. It is useful to note that the conditional expectation of the error term in the equation of interest is simply a function, $f(.)$, of the residual from the selection equation, $\nu_i$. 
The approach followed here is similar to the parametric two-step approach of Heckman (1976, 1979). Our strategy is to exploit the distributional assumption regarding \( v_n \) and estimate \( \gamma / \sigma_v \) by Tobit. We then approximate \( E[v_i | v_n] = f(v_i) \) by \( \sum_{k=1}^{K} \alpha^k \hat{v}_i^k \), where the \( \hat{v}_i \)'s are the generalized residuals from the first step Tobit estimation and \( K \) is the number of terms in the approximating series. The second step is to estimate Equation 6.3 by OLS, setting \( K \) equal to a fixed number. By including a polynomial in the Tobit residuals, we have accounted for the correlation between \( \varepsilon_i \) and \( H_i \) operating through \( v_n \). Therefore, exploiting the variation in \( H_i \) for the subsample \( H_i > 0 \) provides consistent OLS estimates of \( (\beta, \theta) \). Provided \( K \) is treated as known, these estimates are \( \sqrt{n} \) consistent and it is straightforward to compute the second step covariance matrix.

Also, this procedure is somewhat more robust than Heckman's in that the distributional assumptions concerning the error term, \( \varepsilon_n \) in the earnings equation are relaxed.

6.1.3 Results
The first step in obtaining consistent estimates of the parameters in the earnings equations is to estimate the reduced form hours equations by Tobit. The Tobit results for the reduced form labor and crime participation equations are given in Table 12. When interpreting these results, we consider the marginal effect of exogenous variables on the latent variable, desired hours in an activity. In the second stage of estimation, we include a fourth order polynomial in the Tobit residuals in the respective earnings equations to approximate the selection correction term. The results of the second stage estimation are given in Table 13.
The Tobit results for desired hours in the (legitimate) labor market show support for both human and social capital theory. Human capital theory predicts that individuals who have at least a high school education (ED) desire to work more hours per year compared to those who do not. Consistent with this, we find that ED has a positive and significant effect on desired hours of work. These results also indicate support for social capital theory. The desired hours worked in a year is greater for individuals who are white (WHITE) and come from a family with a high socioeconomic status (SES) compared to individuals who are not white and come from low socioeconomic status families. Having no mother when growing up (NMUM) is found to have a negative affect on the desired hours of work. These results are consistent with a model in which white, two parent families with high socioeconomic status endow their children with more social capital than do their poor, nonwhite single parent counterparts. Social capital theory also suggests that marriage is an important institution bonding individuals to their community. Consistent with this, we find that men who are married (MARRY) or are in common law marriages (DEFACTO) wish to work more hours compared to single men. Individuals who have yet to complete their education (SCHOOL) want to work less hours than those who have completed their education. The number of children an individual has (NUMKIDS), and moving out of the parental home (MOVE), have an insignificant affect on the desired hours of work.
Table 12  
*Tobit Estimates of the Selection Equations*  

<table>
<thead>
<tr>
<th>Variable</th>
<th>Work</th>
<th>Crime</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>1054.5</td>
<td>-277.21</td>
</tr>
<tr>
<td></td>
<td>(17.31)</td>
<td>(-6.59)</td>
</tr>
<tr>
<td>ED</td>
<td>297.53</td>
<td>-101.83</td>
</tr>
<tr>
<td></td>
<td>(6.12)</td>
<td>(-3.21)</td>
</tr>
<tr>
<td>SCHOOL</td>
<td>-802.31</td>
<td>47.44</td>
</tr>
<tr>
<td></td>
<td>(-12.26)</td>
<td>(1.10)</td>
</tr>
<tr>
<td>MARRY</td>
<td>542.30</td>
<td>-90.54</td>
</tr>
<tr>
<td></td>
<td>(8.72)</td>
<td>(-2.08)</td>
</tr>
<tr>
<td>NOMUM</td>
<td>-430.18</td>
<td>383.63</td>
</tr>
<tr>
<td></td>
<td>(-2.93)</td>
<td>(4.65)</td>
</tr>
<tr>
<td>WHITE</td>
<td>314.51</td>
<td>31.56</td>
</tr>
<tr>
<td></td>
<td>(6.82)</td>
<td>(1.04)</td>
</tr>
<tr>
<td>SES</td>
<td>131.33</td>
<td>-53.58</td>
</tr>
<tr>
<td></td>
<td>(2.98)</td>
<td>(-1.84)</td>
</tr>
<tr>
<td>DEFACTO</td>
<td>198.32</td>
<td>195.40</td>
</tr>
<tr>
<td></td>
<td>(2.70)</td>
<td>(4.41)</td>
</tr>
<tr>
<td>MOVE</td>
<td>-110.81</td>
<td>18.34</td>
</tr>
<tr>
<td></td>
<td>(-1.31)</td>
<td>(0.33)</td>
</tr>
<tr>
<td>NUMKIDS</td>
<td>6.37</td>
<td>-11.28</td>
</tr>
<tr>
<td></td>
<td>(0.37)</td>
<td>(-0.97)</td>
</tr>
<tr>
<td>$\sigma^2$</td>
<td>982.63</td>
<td>509.41</td>
</tr>
</tbody>
</table>

*Figures in parentheses are t-ratios.*

The results for the (reduced form) Tobit model of desired hours in criminal income producing activities also shows support for both human and social capital hypotheses. As predicted by the human capital approach, individuals with at least a high school education desire to spend less time in crime than those who have acquired less education. The notion of 'the devil makes work for idle hands' also finds limited support in that being in school has a positive but insignificant affect on desired hours in crime. In support of social capital theory, we find that men from high socioeconomic status backgrounds wish to spend less time in crime compared to those from low socioeconomic backgrounds, as
do men who are married and those who had a mother while growing up. An interesting result is that men in common law marriages wish to spend more time in income generating illegal activities than those who are not in common law marriages. This is consistent with social control theory if common law status (as opposed to married) is interpreted as indicating weaker social bonds. It is also of interest to note that being white does not reduce the desired hours spent in criminal income producing activities; it has a positive and insignificant effect. As with desired hours in legitimate income producing activities, the number of children an individual has and moving out of the parental home have an insignificant effect on the desired hours in crime.

The earnings equations for criminal and legitimate activities are estimated using a fourth order polynomial in the respective Tobit residuals to approximate the correlation between the residuals of the selection equation and the earnings equation, $E[\varepsilon_i|v_i]$. The results of this estimation are given below in Table 13.

The parameter estimates for earnings in legitimate labor market activities are consistent with the predictions of human capital theory. Earnings are a concave function of time. The accumulation of human capital (having at least a high school education) results in an income profile with a lower starting income and a steeper slope. Being in school has a negative affect on annual income. In addition to the human capital theory, we find evidence of social capital working through social networks: the marginal income generated by working another hour depends positively on social capital. Assuming the
mean level of social capital over the sample, the magnitude of this affect is the same as that of achieving a high school degree or better.

The results in Table 13 indicate that annual earnings in crime are an increasing function of time spent in that activity. Increasing returns to time in crime may be evidence of some fixed cost associated with engaging in crime, or accumulation of crime specific human capital.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Work</th>
<th>Crime</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>0.5936 (0.035)</td>
<td>0.1849 (0.228)</td>
</tr>
<tr>
<td>HOURS(_t)</td>
<td>0.0702 (4.22)</td>
<td>0.0189 (0.786)</td>
</tr>
<tr>
<td>HOURS(_t^2)</td>
<td>-1.985*10(^{-6}) (4.99)</td>
<td>5.4316*10(^{-5}) (2.822)</td>
</tr>
<tr>
<td>L(_t)*S(_t)</td>
<td>0.00010 (1.954)</td>
<td></td>
</tr>
<tr>
<td>ED</td>
<td>-19.58 (-1.586)</td>
<td></td>
</tr>
<tr>
<td>L(_t)*ED</td>
<td>0.011 (1.758)</td>
<td></td>
</tr>
<tr>
<td>SCHOOL</td>
<td>-1.1604 (-0.207)</td>
<td></td>
</tr>
<tr>
<td>(\nu)</td>
<td>-2.7630*10(^{-3}) (-0.350)</td>
<td>1.2314*10(^{-2}) (0.272)</td>
</tr>
<tr>
<td>(\nu^2)</td>
<td>5.0240*10(^{-6}) (0.896)</td>
<td>1.2172*10(^{-5}) (0.121)</td>
</tr>
<tr>
<td>(\nu^3)</td>
<td>-1.2586*10(^{-9}) (-0.389)</td>
<td>-5.0680*10(^{-8}) (-0.124)</td>
</tr>
<tr>
<td>(\nu^4)</td>
<td>-1.4990*10(^{-12}) (-0.936)</td>
<td>1.5611*10(^{-11}) (0.738)</td>
</tr>
</tbody>
</table>

* Figures in parentheses are t-ratios.
6.1.4 Discussion of Results

A natural starting point for a discussion of the earnings equations estimates is to compare the fitted earnings with actual earnings from legitimate activities, as reported in Chapter 5. To facilitate this process, the relevant information from Chapter 5 is reproduced in the following tables.

Table 14 compares fitted and actual average earnings profiles (averaged over those working) by level of education. We find that our simple model of legitimate earnings does a good job of capturing the earnings patterns displayed in the data. In particular, human capital does determine earning in the fitted profiles. This reflects the significance of the education dummy interacted with hours worked.

<table>
<thead>
<tr>
<th>Year</th>
<th>No High School Diploma</th>
<th>High School Graduate</th>
<th>College Graduate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual</td>
<td>Estimated</td>
<td>Actual</td>
</tr>
<tr>
<td>77</td>
<td>8,381</td>
<td>8,247</td>
<td>7,957</td>
</tr>
<tr>
<td>78</td>
<td>9,287</td>
<td>9,134</td>
<td>10,298</td>
</tr>
<tr>
<td>79</td>
<td>10,633</td>
<td>10,499</td>
<td>11,604</td>
</tr>
<tr>
<td>80</td>
<td>11,144</td>
<td>11,771</td>
<td>13,009</td>
</tr>
<tr>
<td>81</td>
<td>12,424</td>
<td>13,482</td>
<td>13,505</td>
</tr>
</tbody>
</table>

Table 15 contains the estimated and actual legitimate earnings profiles for individuals who are categorized as criminal and noncriminal. For the purposes of comparison with the data in Chapter 5, criminals are considered to be all individuals who are arrested at least once
for either consumption or income crimes during the period 1976-1984. Once again, we find that our legitimate earnings model does a good job of characterizing the actual data. It is noteworthy that after controlling for level of education, conditional on working, criminals and noncriminals do not appear to differ markedly in earnings in legitimate activities.

<table>
<thead>
<tr>
<th>Year</th>
<th>Criminal</th>
<th>Noncriminal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual</td>
<td>Estimated</td>
</tr>
<tr>
<td>77</td>
<td>7,931</td>
<td>7,623</td>
</tr>
<tr>
<td>78</td>
<td>10,270</td>
<td>9,244</td>
</tr>
<tr>
<td>79</td>
<td>11,583</td>
<td>10,618</td>
</tr>
<tr>
<td>80</td>
<td>12,454</td>
<td>12,185</td>
</tr>
<tr>
<td>81</td>
<td>12,724</td>
<td>13,323</td>
</tr>
</tbody>
</table>

Following the format of Chapter 5, Tables 16 and 17 consider whether the findings in Tables 14 and 15 reflect differences in the number of hours worked, or the average hourly wage. As with the tabulations in Chapter 5, our estimates indicate that investment in human capital in the form of education is rewarded by higher market wages.
Table 16

Average Hourly Wage by Level of Education

<table>
<thead>
<tr>
<th>Year</th>
<th>No High School Diploma</th>
<th>High School Graduate</th>
<th>College Graduate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual</td>
<td>Estimated</td>
<td>Actual</td>
</tr>
<tr>
<td>77</td>
<td>4.82</td>
<td>4.62</td>
<td>4.70</td>
</tr>
<tr>
<td>78</td>
<td>5.24</td>
<td>4.95</td>
<td>5.34</td>
</tr>
<tr>
<td>79</td>
<td>5.53</td>
<td>5.49</td>
<td>5.78</td>
</tr>
<tr>
<td>80</td>
<td>6.09</td>
<td>6.25</td>
<td>6.3</td>
</tr>
<tr>
<td>81</td>
<td>6.51</td>
<td>6.87</td>
<td>6.59</td>
</tr>
</tbody>
</table>

Table 17 shows that we find no evidence that criminals face a lower legitimate hourly reward than noncriminals.

Table 17

Average Hourly Wage by Criminal Status

<table>
<thead>
<tr>
<th>Year</th>
<th>Criminal</th>
<th>Noncriminal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual</td>
<td>Estimated</td>
</tr>
<tr>
<td>77</td>
<td>4.95</td>
<td>4.59</td>
</tr>
<tr>
<td>78</td>
<td>5.54</td>
<td>4.95</td>
</tr>
<tr>
<td>79</td>
<td>5.92</td>
<td>5.52</td>
</tr>
<tr>
<td>80</td>
<td>6.33</td>
<td>6.29</td>
</tr>
<tr>
<td>81</td>
<td>6.63</td>
<td>6.91</td>
</tr>
</tbody>
</table>

Conversely, Table 18 indicates that individuals who report criminal income producing activity, but are not arrested during the period 1977-1984 (noncriminals), do not face a lower illegitimate hourly reward than individuals who were arrested (criminals).
Table 18

Estimated Average Hourly Wage in Crime and Work

<table>
<thead>
<tr>
<th>Year</th>
<th>Criminal Crime</th>
<th>Criminal Work</th>
<th>Noncriminal Crime</th>
<th>Noncriminal Work</th>
</tr>
</thead>
<tbody>
<tr>
<td>77</td>
<td>3.74</td>
<td>4.59</td>
<td>3.95</td>
<td>4.63</td>
</tr>
<tr>
<td>78</td>
<td>3.63</td>
<td>4.95</td>
<td>3.39</td>
<td>5.03</td>
</tr>
<tr>
<td>79</td>
<td>3.24</td>
<td>5.52</td>
<td>3.65</td>
<td>5.59</td>
</tr>
<tr>
<td>80</td>
<td>3.79</td>
<td>6.29</td>
<td>4.66</td>
<td>6.37</td>
</tr>
<tr>
<td>81</td>
<td>4.12</td>
<td>6.91</td>
<td>4.74</td>
<td>7.03</td>
</tr>
</tbody>
</table>

6.1.4 Summary

One of the more salient features of the earnings equations estimates is that criminals and noncriminals do not differ markedly in their earning ability in either the legitimate or illegitimate sectors. This suggests that lower earning ability in legitimate activities does not explain the decision to participate in crime. While we find no evidence in support of a human capital theory of crime, we do find support for the human capital theory of earnings. Investment in human capital is rewarded in the labor market by higher wages. Significantly, the earnings premium associated with investment in human capital is of the same order of magnitude as the wage premium for investing in social capital. This supports our hypothesis that the social networks that are part of social capital serve to improve wages.

Another revealing feature of our results is that income from crime displays increasing returns, while income from legitimate work displays diminishing returns with respect to
time spent in that activity. From this characterization of earnings profiles, we would expect individuals who spend any time in crime to specialize in crime. However, eighty percent of people who engage in crime also work in the legitimate sector. Using the coefficients from our legitimate and illegitimate earnings equations, a person from our sample who is not in school and has less than a high school education could earn the same income working in the legitimate sector 42 hours a week as he could working 21 hours in crime and 21 hours in the legitimate sector. But we do not observe this behavior. Criminals only spend an average of one and a half hours per week, or eighty hours per year in criminal activities, compared to almost 36 hours per week working at a legitimate job (this represents an average for those working). This suggests there are costs associated with crime that are not captured by the earnings equations. Another way of stating this is there are benefits associated with not engaging in crime that are not captured by the earnings equations. According to the model of social capital, these benefits are represented by the utility value of social capital, such as social acceptance and reputation. We test this conjecture in the next section by estimating the Euler equations associated with optimal allocation of time to criminal and legitimate activities and consumption.

6.2 The Euler Equations

6.2.1 The Model

In Chapter 3, we derived a system of Euler equations which describe an individual’s per period optimal choice of time allocations \((L, C)\) and consumption \((X_t)\). We now wish to develop a strategy to econometrically implement this system. To do this, we will need to
parameterize preferences and the earnings equations, characterize the stochastic framework, and address the issue of unobservability of variables that enter the Euler equations. Initially, we abstract from data issues and show how the implications of our theoretical model, in conjunction with our parametric assumptions and stochastic framework, can be employed to form a Generalized Method of Moments estimator (Hansen, 1982) of preferences. We then show how this framework can be modified to accommodate the unobserved expected responses. The resulting estimator falls within the class of Simulated Method of Moments estimators (McFadden and Ruud, 1994; McFadden, 1989; Pakes and Pollard, 1989).

To begin, we assume that we have a panel of $T$ periods of observations on a random sample of $N$ individuals and that all arguments of the Euler equations are observed without error. Assume that households are homogeneous in preferences and that the utility and earnings functions have a known parametric form. Specifically, we assume that the earnings in the legal sector and crime are parameterized as above and that utility has the following form:

$$U(X_t, t, S_t) = \alpha_1 \ln X_t + \alpha_2 \ln l_t + \alpha_3 \ln S_t + \frac{T}{2} \left\{ \beta_{11} (\ln X_t)^2 + \beta_{22} (\ln l_t)^2 + \beta_{33} (\ln S_t)^2 \right\}$$

$$+ \beta_{12} \ln X_t \ln l_t + \beta_{13} \ln X_t \ln S_t + \beta_{23} \ln l_t \ln S_t.$$

This specification, the transcendental logarithmic utility function, represents a second order approximation to any arbitrary utility function. It does not impose restrictions on

---

1 We omit time in consumption crime from the model estimated since a large proportion of observations take on a zero value and the utility function we have assumed is not well behaved at zero.
additivity and homotheticity associated with other utility functions such as Cobb-Douglas or CES. The corresponding marginal utility functions are:

\[ U_1(X_t, t_t, S_t) = \left( \alpha_1 + \beta_{11} \ln X_t + \beta_{12} \ln l_t + \beta_{13} \ln S_t \right) / X_t, \quad (6.7) \]

\[ U_2(X_t, t_t, S_t) = \left( \alpha_2 + \beta_{22} \ln l_t + \beta_{12} \ln X_t + \beta_{23} \ln S_t \right) / l_t, \quad \text{and} \quad (6.8) \]

\[ U_3(X_t, t_t, S_t) = \left( \alpha_3 + \beta_{33} \ln S_t + \beta_{13} \ln X_t + \beta_{23} \ln l_t \right) / S_t \quad \text{for } t = 1, \ldots, T. \quad (6.9) \]

Assuming the earnings equations from above, the marginal income functions are:

\[ \frac{\partial W_L(L_t, S_t)}{\partial L_t} = \eta_1 + 2\eta_2 L_t + \eta_3 S_t + \eta_5 ED_t, \]

\[ \frac{\partial W_L(L_t, S_t)}{\partial S_t} = \eta_3 L_t, \quad \text{and} \]

\[ \frac{\partial W_C(C_t)}{\partial C_t} = \mu_1 + 2\mu_2 C_t \quad \text{for } t = 1, \ldots, T. \]

We take the estimated earnings equation parameters to be the true values, and the parameters governing the law of motion for social capital accumulation to be those obtained using principal components. Sample data is used to calibrate the probability of arrest at 0.06. We assume a real rate of interest of 3\%, and a time rate of preference of 0.95. Substituting these parameters and the marginal utility and income functions into the Euler equations from Chapter 3,
\[ X_t : U_1(t) - \beta(1+r)\left[pU_1^1(t+1) + (1-p)U_1^0(t+1)\right] = 0 \]

\[ L_t : U_1(t)\frac{\partial W_L(L_t, S_t)}{\partial L_t} - U_2(t) + \beta \gamma (1-p) \left[ \frac{(1-\delta)}{\gamma} - \frac{1-\delta - \alpha C_{t+1}^0}{\alpha S_{t+1}^0} \right] U_2^0(t+1) \]

\[ + \left( \frac{\partial W_L(L_{t+1}^0, S_{t+1}^0)}{\partial S_{t+1}^0} + \frac{1-\delta - \alpha C_{t+1}^0}{\alpha S_{t+1}^0} \frac{\partial W_C(C_{t+1}^0)}{\partial C_{t+1}} \right) U_1^0(t+1) \right] + U_1^0(t+1) \right) = 0 \]

\[ C_t : U_1(t)\frac{\partial W_C(C_t)}{\partial C_t} - U_2(t) - \beta \alpha p S_t \left[ \frac{(1-\delta)}{\gamma} - \frac{1-\delta - \alpha C_{t+1}^l}{\alpha S_{t+1}^l} \right] U_2^l(t+1) \]

\[ + \left( \frac{\partial W_L(L_{t+1}^l, S_{t+1}^l)}{\partial S_{t+1}^l} + \frac{1-\delta - \alpha C_{t+1}^l}{\alpha S_{t+1}^l} \frac{\partial W_C(C_{t+1}^l)}{\partial C_{t+1}} \right) U_1^l(t+1) \right] + U_1^l(t+1) \right) = 0 \]

result in the individual’s per period optimal choice of time allocations \((L_t, C_t)\) and consumption \((X_t)\) being parameterized by \(\theta_0 = (\alpha_1, \alpha_2, \alpha_3, \beta_{11}, \beta_{22}, \beta_{33}, \beta_{12}, \beta_{13}, \beta_{23})\).

### 6.2.2 Theory and Method

The above system of Euler equations is deterministic. We next introduce a stochastic framework and show how the system of Euler equations together with this framework can...
be used to formulate a nonlinear instrumental variables estimator that belongs to the class of Generalized Method of Moments estimators.

We begin by introducing some notation to simplify exposition. Let $x_{it}$ denote the variables entering the $ith$ individual's Euler equations in period $t$, and let $y_{it}$ be those variables dated $t+1$. Each of these Euler equations can be written in the form of $f_j(x_{it}, \theta_0) - g_j(y_{it}, \theta_0)$, $j=1,2,3$, where $f(\cdot)$ is the observed response function which depends on current period variables, and $g(\cdot)$ is the expected response function, which depends on next periods variables, and $\theta_0$ is the $pxl$ vector of parameters to be estimated. We introduce a stochastic framework by assuming that variables determined outside the model, whose future values are unknown and random, cause agents to make idiosyncratic errors in choosing their utility maximizing bundles. Using the translog utility specification and taking the earnings and social capital accumulation parameters as given, we represent the $ith$ individual's system of equations as:

$$f(x_{it}, \theta_0) - g(y_{it}, \theta_0) = u_{it}$$

where $f(x_{it}, \theta_0) = (f_1(x_{it}, \theta_0), f_2(x_{it}, \theta_0), f_3(x_{it}, \theta_0))^\prime$ is a 3 dimensional vector of observed response functions $g(y_{it}, \theta_0) = (g_1(y_{it}, \theta_0), g_2(y_{it}, \theta_0), g_3(y_{it}, \theta_0))^\prime$ is a 3 dimensional vector of expected response functions, and $u_{it} = (u_{it,1}, u_{it,2}, u_{it,3})^\prime$ is a vector of random errors associated with the period $t$ Euler equations. These errors are idiosyncratic so that at any point in time, the expectation of this disturbance term over individuals is zero. We
also assume that the disturbances are independently distributed across individuals and time.

Suppose that there exist conditional moment restrictions of the form, $E[u_t | z_{it}] = 0$, where $z_{it}$ are observable data which are uncorrelated with the disturbances $u_t$. Then these moment restrictions can be used to form a nonlinear instrumental variables estimator of the preference parameters (Amemiya (1974), Jorgenson and Laffont (1974), and Gallant (1977)). Hansen (1982) points out that the NLIV estimator of this form can be interpreted as the optimal Generalized Method of Moment estimators when $u_t$ are serially uncorrelated and conditionally homoskedastic.

Under mild regularity assumptions, sufficient conditions for the GMM estimator to be consistent and asymptotically normal are:

(i) the instruments are of maximum rank

(ii) the conditional expectation of the residuals, given the instruments, is zero if and only if $\theta = \theta_0$.

Our estimation strategy is to exploit the orthogonality conditions between the Euler equations and the instruments, $z_{it}$, to estimate the elements of $\theta_0$ by the Generalized Method of Moments. Given panel data covering $T$ years for each of the $N$ individuals, the population orthogonality conditions for these years can be written as:
\[ E_N \left[ \sum_{i=1}^{N} (f(x_i', \theta_0) - g(y_i, \theta_0)) \otimes z_i \right] = E_N [M(x_i, y_i, z_i, \theta_0)] = 0 \]

where \( x_i = (x_{i1}', x_{i2}', \ldots, x_{iT}')', \ y_i = (y_{i1}', y_{i2}', \ldots, y_{iT}')' \) and \( z_i = (z_{i1}', z_{i2}', \ldots, z_{iT}')' \) and \( E_N \) is the expectations operator over individuals. Suppose that a law of large numbers can be applied to \( M(x_i, y_i, z_i, \theta_0) \) for all admissible \( \theta \) so that the sample mean converges to the population mean:

\[ \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^{N} [M(x_i, y_i, z_i, \theta_0)] \overset{as}{\longrightarrow} E_N [M(x_i, y_i, z_i, \theta_0)] \]

The GMM estimator of \( \theta_0 \) minimizes a quadratic form of the sample mean and is defined as:

\[ \theta_{mm} = \text{ARGMIN}_\theta \left\{ \left\{ \frac{1}{N} \sum_{i=1}^{N} M(x_i, y_i, z_i, \theta) \right\}' W_N^{-1} \left\{ \frac{1}{N} \sum_{i=1}^{N} M(x_i, y_i, z_i, \theta) \right\} \right\} \]

where \( W_N \) is a symmetric positive definite weighting matrix which satisfies:

\[ \lim_{N \to \infty} W_N \overset{as}{\longrightarrow} W_0 . \]

Suppose that a central limit theorem can be applied to the GMM disturbance \( u_i \otimes z_i = \epsilon_i \)

where \( u_i = (u_{i1}', u_{i2}', \ldots, u_{iT}')', z_i = (z_{i1}', z_{i2}', \ldots, z_{iT}')' \) and \( \epsilon_i = (\epsilon_{i1}', \epsilon_{i2}', \ldots, \epsilon_{iT}')' \), so that \( N^{-1/2} \sum_{i=1}^{N} \epsilon_i \) has an asymptotic normal distribution with mean zero and covariance
matrix, $W$, in large samples. Let $\Gamma = E[\partial M(x_i, y_i, z_i, \theta)/\partial \theta]$ be the expectation of the $q \times p$
matrix of derivatives of $M(x_i, y_i, z_i, \theta)$ with respect to $\theta$ and assume that $G$ has full
column rank. Hansen (1982) shows that under fairly general regularity conditions,

$$\sqrt{N}(\theta^* - \theta_0) \overset{d}{\rightarrow} N\left(0, (\Gamma' W_0 \Gamma)^{-1} (\Gamma' W_0 \Omega W_0 \Gamma) (\Gamma' W_0 \Gamma)^{-1}\right).$$

The GMM estimator is consistent for arbitrary distance matrices. However different
choices of distance matrices produce different GMM estimators when the number of
moment conditions exceed the number of parameters to be estimated ($q > p$). The choice
of weighting matrix that produces the efficient or optimal GMM estimator is $W_0 = \Omega^{-1}$.

With this choice of distance matrix,

$$\sqrt{N}(\theta^* - \theta_0) \overset{d}{\rightarrow} N\left(0, (\Gamma' \Omega^{-1} \Gamma)^{-1}\right).$$

This covariance matrix is consistently estimated by $\left(\Gamma_N', \Omega_N^{-1}, \Gamma_N\right)^{-1}$, where

$$\Omega_N^{-1} = \left(\frac{1}{N} \sum_{i=1}^{N} M(x_i, y_i, z_i, \hat{\theta}) M(x_i, y_i, z_i, \hat{\theta})^\prime\right)^{-1} = W_N,$$

$$\Gamma_N = \left(\frac{1}{N} \sum_{i=1}^{N} \partial M(x_i, y_i, z_i, \theta^*)/\partial \theta\right),$$

and $\hat{\theta}$ is any consistent estimator of $\theta$. Consistent first step estimates of $\theta$ can be obtained
by using the identity matrix for the weighting matrix, $W_N$. 
When the number of restrictions exceeds the number of parameters, the validity of moment conditions implied by the Euler equations can be used as a general specification test for GMM. In this case, there are linear combinations of sample orthogonality conditions that have a nondegenerate asymptotic distribution. These linear combinations of sample orthogonality conditions can be used to obtain an asymptotically valid test statistic of the model restrictions. In particular, Hansen (1982) shows that

\[ \tau_N = N \left[ \frac{1}{N} \sum_{i=1}^{N} M(x_i, y_i, z_i, \theta^*) \right]' W_N \left[ \frac{1}{N} \sum_{i=1}^{N} M(x_i, y_i, z_i, \theta^*) \right] \]

has an asymptotic chi-squared distribution with degrees of freedom equal to the number of overidentifying restrictions if \( \theta^* \) is the optimal GMM estimator and \( W_N \) is a consistent estimator of \( \Omega^{-1} \).

In practice, implementing GMM as an estimator for the parameters in our Euler equations is hampered by the fact that observed future welfare is state contingent, while agents' decisions are based on ex-ante expectations of the future. For those who engage in crime, there are two possible future states of the world - apprehension and escaping apprehension. Ex-post, only one state is realized for each individual and subsequently observed by the econometrician. Since the (unobserved) choice in the state not realized enters the Euler equations through \( g(y_u, \theta_0) \), we are faced with an omitted regressor problem in the expected response function. We resolve this issue by replacing the
expected response function with an unbiased simulator. McFadden (1989) proposes this simple modification of the conventional Method of Moments estimator as the basis for the Method of Simulated Moments.

To demonstrate the issue, let us define the following terms:

\[ E_N \left[ \frac{1}{N} \sum_{i=1}^{N} \left( f(x_i, \theta_0) - g(y_i, \theta_0) \right) \right] = E_N \left[ M_1(x_i, z_i, \theta_0) - M_2(y_i, z_i, \theta_0) \right] = 0 \]

\[ \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^{N} M_1(x_i, z_i, \theta_0) \xrightarrow{a.s.} E_N \left[ M_1(x_i, z_i, \theta_0) \right] \]

\[ \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^{N} M_2(y_i, z_i, \theta_0) \xrightarrow{a.s.} E_N \left[ M_2(y_i, z_i, \theta_0) \right] \]

so that we may view the GMM estimator \( \theta_{mm} \), of the unknown parameter vector \( \theta_0 \), as minimizing the generalized quadratic distance from zero of the empirical moments:

\[ \left( \frac{1}{N} \sum_{i=1}^{N} M_1(x_i, z_i, \theta) - M_2(y_i, z_i, \theta) \right)' W_N \left( \frac{1}{N} \sum_{i=1}^{N} M_1(x_i, z_i, \theta) - M_2(y_i, z_i, \theta) \right) \]

\( M_2(.) \) is linear in the expected response function, \( g(y_i, \theta) \), which may depend on variables which are not observed. The method of simulated moments replaces \( M_2(.) \) with a simulator \( \mu_2(.) \) that is asymptotically conditionally unbiased, given \( x_i \) and \( W_N \), and independent across observations. The MSM estimator is given by any argument \( \theta_{mm} \) satisfying
\[
\frac{1}{N} \sum_{i=1}^{N} M_1(x_i, z_i, \theta_{sm}) - \mu_2(y_i, z_i, \theta_{sm}) \right] W_N \left[ \frac{1}{N} \sum_{i=1}^{N} M_1(x_i, z_i, \theta_{sm}) - \mu_2(y_i, z_i, \theta_{sm}) \right] \leq \inf_{\theta \in \Theta} \left[ \frac{1}{N} \sum_{i=1}^{N} M_1(x_i, z_i, \theta) - \mu_2(y_i, z_i, \theta) \right] W_N \left[ \frac{1}{N} \sum_{i=1}^{N} M_1(x_i, z_i, \theta) - \mu_2(y_i, z_i, \theta) \right] + O(1)
\]

Sufficient conditions for the MSM estimator to be consistent and asymptotically normal involve the same regularity assumptions and conditions on instruments as classical GMM, in addition to the two following assumptions that concern the simulator, \( \mu_2(\cdot) \):

i) the simulation bias, conditional on \( W_\theta \) and \( x_{it} \), is zero, and

ii) the simulation residual process is uniformly stochastically bounded and equicontinuous in \( \theta \).

McFadden (1989) shows that if the simulation errors are independent across observations and sufficiently regular in \( \theta \), the variance introduced by simulation will be controlled by the law of large numbers operating across observations. This makes it unnecessary to consistently estimate each expected response in order for the MSM estimator to be CAN. McFadden also points out that for the simulation residual process to be well behaved usually requires the Monte-Carlo data used to construct the expected response function not be redrawn when \( \theta \) is changed.

In our application, we simulate the expected response function in the following way. For an individual who is apprehended, we take Monte-Carlo draws of unobserved variables corresponding to the state not apprehended from the distribution of those who were in
fact not apprehended, conditioning on the state variable, social capital. Symmetrically, we replace the unobserved data for those not apprehended by draws from the empirical conditional distribution of those who were apprehended. We use these draws to form a simulator of the moment function and minimize the generalized distance of the moment conditions from zero.

6.2.3 Results

The system of Euler equations is estimated using SMM on 423 individual’s over the period 1977 to 1981. The coefficient on the logarithm of social capital is normalized at unity, leaving eight coefficients to be estimated. With three equations and eleven instruments, the number of overidentifying restrictions is twenty-five. The Hansen test statistic for overidentifying restrictions is 5.23, compared to a $\chi^2_{0.95,25} = 37.65$, so we accept the null hypothesis of the system being overidentified. The SMM estimates of the preference parameters are presented in Table 19.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\ln X_t$</td>
<td>0.2256</td>
<td>0.24373</td>
</tr>
<tr>
<td>$\ln \ell_t$</td>
<td>0.2061</td>
<td>0.51110</td>
</tr>
<tr>
<td>$(\ln X_t)^2$</td>
<td>0.0007</td>
<td>0.00004</td>
</tr>
<tr>
<td>$(\ln \ell_t)^2$</td>
<td>0.1084</td>
<td>0.02641</td>
</tr>
<tr>
<td>$(\ln S_t)^2$</td>
<td>0.1910</td>
<td>0.07842</td>
</tr>
<tr>
<td>$\ln X_t \ln \ell_t$</td>
<td>-0.0220</td>
<td>0.00108</td>
</tr>
<tr>
<td>$\ln X_t \ln S_t$</td>
<td>-0.0077</td>
<td>0.002037</td>
</tr>
<tr>
<td>$\ln S_t \ln \ell_t$</td>
<td>-0.2141</td>
<td>0.04151</td>
</tr>
</tbody>
</table>
Six of the eight coefficients are found to be statistically significant. It is noteworthy that all three terms involving social capital are found to be significantly different from zero, supporting the hypothesis that social capital influences preferences.

6.2.3 Discussion of Results

Examining the estimates of the translog preference parameters in Table 3, we find the coefficients on the interaction terms between consumption and leisure ($\beta_{12}$), consumption and social capital ($\beta_{13}$), and leisure and social capital ($\beta_{23}$) are all significant. This indicates that utility is not contemporaneously separable in any of its arguments. Nonseparability between consumption and leisure is an important result since separability is often assumed. Our estimates imply that consumption and leisure are compliments in utility. This is consistent with the findings of Hotz, Kydland and Sédlacek (1988), and Sickles and Yazbeck (1996). Other studies, however, find evidence that these goods are substitutes (Altonji, 1986; Ghez and Becker, 1975; Thurow, 1969). The relationships between consumption and social capital, and leisure and social capital, are also found to be complementary. These findings are in keeping with a model in which individuals value consuming social capital, leisure, and consumption goods jointly.

Table 20 contains our estimates of marginal utilities for each time period. These are obtained by evaluating equations 6.7 - 6.9 at sample averaged (across individuals) data. The marginal utilities associated with consumption, leisure, and social capital are positive in all time periods. We find that the value of an incremental increase in the consumption
good rises over the life-cycle for our sample of young men. The marginal utility of a thousand dollar increase in consumption is estimated to be on the order 0.08. This is comparable with Sickles and Yazbeck’s study, which finds the marginal utility of a thousand dollar increase in consumption for the 58 - 63 year old men they studied to be around 0.03. Our results show that the marginal utility of leisure declines steeply between the ages of nineteen and twenty, but remains fairly steady thereafter. Based on these estimates, the marginal utility of an additional thousand hours of leisure is approximately 0.0058. Sickles and Yazbeck’s results indicate a figure on the order of 0.026. This may be evidence that individuals place a higher value on leisure time as they draw closer to the end of their life.

<table>
<thead>
<tr>
<th>Age</th>
<th>Consumption</th>
<th>Leisure</th>
<th>Social Capital</th>
</tr>
</thead>
<tbody>
<tr>
<td>19</td>
<td>8.13*10^{-5}</td>
<td>7.17*10^{-6}</td>
<td>4.29*10^{-4}</td>
</tr>
<tr>
<td>20</td>
<td>7.70*10^{-5}</td>
<td>5.87*10^{-6}</td>
<td>5.08*10^{-4}</td>
</tr>
<tr>
<td>21</td>
<td>7.98*10^{-5}</td>
<td>5.59*10^{-6}</td>
<td>5.54*10^{-4}</td>
</tr>
<tr>
<td>22</td>
<td>8.24*10^{-5}</td>
<td>5.79*10^{-6}</td>
<td>5.69*10^{-4}</td>
</tr>
<tr>
<td>23</td>
<td>8.43*10^{-5}</td>
<td>5.88*10^{-6}</td>
<td>5.83*10^{-4}</td>
</tr>
</tbody>
</table>

We find that the value of an incremental increase in the stock of social capital rises over the life-cycle for our sample of young men. This is consistent with social control theory. Recall that this theory posits that as an individual ages, his ties to legitimate society
strengthen. These social ties create interdependent systems of obligation and restraint that impose significant costs for translating criminal propensities into crime, making the occurrence of crime less likely. The process by which an individual becomes more closely bonded to society is represented in our formulation by the individual building social capital. Social capital has utility value to an individual because in part, it represents reputation and social acceptance. Our results provide evidence that social capital does in fact become more important as our sample ages. Consequently, the cost associated with crime increases with age, making the occurrence of crime less likely.

It is particularly revealing to compare the temporal pattern of the marginal utility of social capital with the age-crime profile. Figure 3 shows a strong inverse relationship between the two profiles, suggesting that the social capital hypothesis does indeed explain the temporal pattern of criminal behavior. For our sample, social capital exhibits increasing marginal utility over the period examined. However, the rate at which additional units increase welfare declines at the age when the age-crime profile flattens out. This pattern suggests that the late teens and early twenties is a crucial time for our sample of young men. During this time, it is increasingly important to form social bonds to legitimate society. The data demonstrates clearly the consequent decline in criminal activity associated with this period of social capital accumulation. After the age of twenty-one however, the profile of the marginal utility of social capital flattens out, as does the age-crime profile. This is suggests individuals who have not made the transition to legitimate culture by twenty one may never do so.
Figure 3.
*The Marginal Utility of Social Capital Versus the Age Crime Profile*

To gauge the relative importance of consumption, leisure, and social capital in terms of utility value, we consider the elasticity of utility with respect to each of these arguments. This is presented in Table 21. These results indicate that utility is most sensitive to changes in social capital and least responsive to changes in consumption. It is also interesting to note the temporal pattern in these elasticities. As these individuals age, their welfare becomes more responsive to changes in their level of social capital and consumption, and less responsive to changes in their level of leisure. Our results suggest not only that the marginal utility of social capital increases with age, but that welfare becomes more responsive to changes in the level of capital stock over the life-cycle. This finding is further support of social control theory.
Table 21

*Responsiveness of Utility to a 1% Increase in Consumption, Leisure and Social Capital (evaluated at each data point and averaged over individuals)*

<table>
<thead>
<tr>
<th>Year</th>
<th>Consumption</th>
<th>Leisure</th>
<th>Social Capital</th>
</tr>
</thead>
<tbody>
<tr>
<td>19</td>
<td>2.11*10⁻³</td>
<td>8.15*10⁻³</td>
<td>1.08*10⁻²</td>
</tr>
<tr>
<td>20</td>
<td>2.59*10⁻³</td>
<td>6.31*10⁻³</td>
<td>1.25*10⁻²</td>
</tr>
<tr>
<td>21</td>
<td>2.68*10⁻³</td>
<td>5.84*10⁻³</td>
<td>1.36*10⁻²</td>
</tr>
<tr>
<td>22</td>
<td>2.76*10⁻³</td>
<td>5.99*10⁻³</td>
<td>1.38*10⁻²</td>
</tr>
<tr>
<td>23</td>
<td>2.84*10⁻³</td>
<td>6.01*10⁻³</td>
<td>1.41*10⁻²</td>
</tr>
</tbody>
</table>

To further explore the role of social capital in explaining participation in crime, we disaggregate our sample. We partitioned our data into quartiles on the basis of the first time period (1977) stock of social capital. We wish to compare the temporal pattern in the marginal utility of social capital for the first and fourth quartiles. Figure 4 shows that the marginal utility of social capital for individuals in the fourth quartile increases over time, just as it does for the whole sample.
The marginal utility of social capital for individuals from the first quartile displays a markedly different temporal pattern, as shown in Figure 5. While the value of an incremental increase in social capital increases over the ages 19 to 21, it falls thereafter. Also, the marginal utility of social capital is always negative for this group.
The latter finding may be an artifact of the assumed functional form for utility. The translog frees up constraints on additivity and homotheticity, which makes it better behaved in terms of global curvature properties than more restrictive functional forms. However, this flexibility often compromises the regularity of the estimated curvatures outside the region in which the data and estimates are centered. This problem has been well documented in the literature of flexible functional forms (Guilkey, et al., 1983; Pollak, et al., 1984; Barnett, 1985: Diewert and Wales, 1987). Alternatively, the temporal pattern in the estimated marginal utility of social capital for men from the first quartile may be revealing something about the behavior of these individuals.

When we compare the two groups' involvement with the criminal justice system, we find that individuals from the first quartile are far more likely to be arrested for an income producing crime in any year. This is reported in Table 22. For these men, who are embedded in a criminal culture, bonds to legitimate society may in fact be considered a 'bad', as reflected by the negative marginal utility associated with social capital. The temporal pattern displayed in the marginal utility of social capital for this group may be evidence of the difficulty these individuals have making the transition from the culture of crime to the culture of legitimate society. The increasing value of the marginal utility of social capital through to the age of twenty-one indicates strengthening ties with the legitimate community. Thereafter, the marginal value of social capital decreases dramatically. Since the value of incremental increases in social capital does not become
positive during the time of strengthening bonds, this pattern is evidence of failure to transition into legitimate society and the consequent absorption into criminal culture.

<table>
<thead>
<tr>
<th>Year</th>
<th>Total (all quartiles)</th>
<th>First Quartile (proportion)</th>
<th>Fourth Quartile (proportion)</th>
</tr>
</thead>
<tbody>
<tr>
<td>77</td>
<td>36</td>
<td>0.33</td>
<td>0.08</td>
</tr>
<tr>
<td>78</td>
<td>26</td>
<td>0.46</td>
<td>0.04</td>
</tr>
<tr>
<td>79</td>
<td>29</td>
<td>0.45</td>
<td>0.10</td>
</tr>
<tr>
<td>80</td>
<td>20</td>
<td>0.40</td>
<td>0.10</td>
</tr>
<tr>
<td>81</td>
<td>23</td>
<td>0.57</td>
<td>0.09</td>
</tr>
</tbody>
</table>

6.2.4 Summary

The results from applying the Method of Simulated Moments to our system of Euler equations has provided evidence of the important role of social capital in the dynamic decision to participate in crime. First and foremost, we find that social capital is a statistically significant component of the preference structure for individuals in our sample. This is consistent with our formulation of social control theory, where social capital has utility value through reputation and social acceptance. Further, utility is nonseparable in its arguments, with social capital and leisure being complements in consumption, as are social capital and our composite consumption good. Consequently, models of crime that omit social capital from preferences will produce biased results.

The translog specification performs well, with estimates of marginal utilities (evaluated at sample means) being positive for all arguments of the utility function in all periods. The
magnitude of the estimated marginal utility of consumption is comparable to other studies, while that of leisure indicates a higher value associated with leisure as people approach the end of their life.

Social control theory predicts that a person's ties to legitimate society strengthens as he ages. In our formulation, social ties are represented by the individual's social capital stock. We find, consistent with social control theory, the marginal utility of social capital increases over the sample period. Moreover, an individual's welfare becomes more responsive to changes in social capital, relative to consumption or leisure, as he ages.

It is the interdependent system of obligation and restraint associated with social ties (or in our formulation, social capital), which impose costs for translating criminal propensities into acts of crime. The social control theory of crime is that increasing bonds to legitimate society impose increasing costs of engaging in crime, making the occurrence of crime less likely as an individual ages. This is precisely the pattern of behavior observed when we compare the age-crime profile for our sample with the (average) marginal utility of social capital. In particular, we find that the late teens to early twenties is a crucial time in the life-cycle for forming social capital and making the transition from youth culture to adult society. The data clearly demonstrates the decline in arrest rates associated with this period of transition. After the age of twenty-one however, the profile of the marginal utility of social capital flattens out, as does the age-crime profile. This suggests that
individuals who have not made the transition to legitimate culture by twenty-one may never do so.

We explore this hypothesis by comparing individuals who began the sample period with differing stocks of social capital. The marginal utility of social capital for individuals from the fourth quartile exhibited the same behavior as the sample average. However, the temporal pattern in the marginal utility of social capital was markedly different for men from the first quartile of initial social capital stock. These individuals are heavily embedded in criminal culture, as evidenced by the disproportionate number of arrests they incurred during the sample period. Not surprisingly, social capital is found to be a ‘bad’ for this group. Nonetheless, the increasing value of the marginal utility of social capital up to the age of twenty-one indicates strengthening ties with legitimate community as these individuals attempt to make the transition into legitimate society. The failure of the marginal value of social capital to become positive coupled with the dramatic decrease in its value after age twenty-one signals the inability of these people to make that transition and their consequent absorption into criminal culture.

These results not only provide evidence of the importance of social capital in the decision to participate in crime. They indicate that a low social capital stock inherited from childhood puts an individual at greater risk of becoming a criminal in adulthood. Also evident is the dynamic nature of the process of absorption into legitimate culture, as represented by social capital accumulation. The late teenage yeas to early twenties is a
crucial time for making the transition to legitimate culture, even for those most disadvantaged in terms of family social capital stock.
CHAPTER 7

TOWARD A MORE GENERAL DYNAMIC MODEL OF CRIME

The results presented in the previous chapter provides strong empirical support for a social capital theory of crime. However, the model developed in Chapter 3 and implemented in Chapter 6 made several restrictive assumptions in order to arrive at an estimable set of Euler equations. Given the support we have found for our approach, we believe that several of the issues we abstract from in earlier chapters merit further investigation. The two issues we focus on in this chapter are the accumulation of human capital, and the endogeneity of the probability of arrest.

Although our data have consistently provided evidence that human capital does determine earnings, we have failed to account for this relationship in our theoretical model. This shortcoming is addressed in the model developed in Section 7.1. We have also neglected the possibility that the probability of arrest is effected by one's actions. In the model presented in Section 7.2, we attempt to account for this effect by allowing the probability of arrest an individual faces to be increasing in the time allocated to criminal endeavors. We show that either incorporating human capital or allowing the probability of arrest to depend on the individual's behavior leads to conditions for optimality which do not have a closed form solution. In Section 7.3, we discuss possible ways to proceed to facilitate estimation of these models.
7.1 Introducing Human Capital into the Dynamic Model of Crime

Human and social capital should not be considered as competing explanations of crime. Both are important components of a life-cycle theory of crime. Accordingly, we extend the model developed in Chapter 3 by introducing human capital and allowing market wages to increase as individuals acquire more human capital. We begin by assuming there is no accumulation of crime specific human capital. While it would be desirable to allow returns from crime to depend on the level of criminal proficiency, it is the difference between rewards from criminal activity and legitimate work that is of interest. Also, there is a question of identification. Each individual has a fixed quantity of resources that he allocates between activities that affect social capital, human capital, or criminal capital. The accumulation of each of these capital stocks is related to the accumulation of the other stocks through the resource constraint. Therefore, we proceed by including human in addition to social capital in our model of crime. The evolution of human capital, $E_t$, is described by:

$$E_{t+1} = (1 - \eta)E_t + \mu L_t$$

where $\eta$ is the rate of depreciation of human capital and $\mu$ describes the technology which transforms labor market experience into human capital. Notice that human capital accrues to an individual who spends time in the labor market irrespective of whether he is arrested, while social capital accumulation occurs only if the individual escapes arrest.
Wages in the legitimate labor market now depend on both the level of social and human
capital in addition to the time spent working each period, such that:

\[
\frac{\partial W_L(L_t, S_t, E_t)}{\partial L_t} = 0,
\frac{\partial W_L(L_t, S_t, E_t)}{\partial S_t} = 0,
\frac{\partial W_L(L_t, S_t, E_t)}{\partial E_t} = 0,
\frac{\partial W_L(0, S_t, E_t)}{\partial L_t} = 0.
\]

The individual's dynamic programming problem is characterized by his value function at
period \( t \), \( V(A_t, S_t, E_t) \), which is the solution to the Bellman equation:

\[
V(A_t, S_t, E_t) = \max_{X_t, C_t, C_t} \left\{ U(X_t, \ell_t, C_t) \right\}
+ \beta \left\{ \min \left\{ \left\{ \frac{pV(A_{t+1}, S_{t+1}, E_{t+1}) + (1-p)V(A_{t+1}, S_{t+1}, E_{t+1})}{\partial C_t} \right\} \right\}
\]

Subject to:
1) \( T = \ell_t + L_t + C_t \)
2) \( C_t = C_t^c + C_t^l \)
3) \( A_{t+1} = (1+r)(A_t + W_L(L_t, S_t, E_t) + W_C(C_t) - X_t) \)
4) \( S_{t+1}^l = \{(1-\delta) - \alpha C_t\}S_t \quad \text{if caught} \)
\( S_{t+1}^0 = (1-\delta)S_t + \gamma L_t \quad \text{if not caught} \)
5) \( E_{t+1} = (1-\eta)E_t + \mu L_t \)

By substituting (1) in for \( \ell_t \), we eliminate \( \ell_t \) as a choice variable. The first order
conditions with respect to \( X_t, L_t, C_t^l \) and \( C_t^c \) are:
\[
\frac{\mathcal{H}(A_t,S_t,E_t)}{\partial X_t} = U_1(t) - \beta(1+r) \left\{ p \frac{\partial V(A_{t+1},S_{t+1}^{-1},E_{t+1})}{\partial A_{t+1}} + (1-p) \frac{\partial V(A_{t+1},S_{t+1}^0,E_{t+1})}{\partial A_{t+1}} \right\} = 0
\] (7.1)

\[
\frac{\mathcal{H}(A_t,S_t,E_t)}{\partial X_t} = -U_2(t) + \beta\gamma(1-p) \frac{\partial V(A_{t+1},S_{t+1}^0,E_{t+1})}{\partial S_{t+1}} + \beta(1+r) \frac{\partial \mathcal{W}_t}{\partial X_t} \left\{ p \frac{\partial V(A_{t+1},S_{t+1}^{-1},E_{t+1})}{\partial A_{t+1}} + (1-p) \frac{\partial V(A_{t+1},S_{t+1}^0,E_{t+1})}{\partial A_{t+1}} \right\}
\] (7.2)

\[
\frac{\partial V(A_t,S_t,E_t)}{\partial C_t} = U_1(t) - U_2(t) - \alpha \beta S_p \frac{\partial V(A_{t+1},S_{t+1}^{-1},E_{t+1})}{\partial S_{t+1}} = 0
\] (7.3)

\[
\frac{\mathcal{H}(A_t,S_t,E_t)}{\partial C_t} = -U_2(t) - \alpha \beta S_p \frac{\partial V(A_{t+1},S_{t+1}^{-1},E_{t+1})}{\partial S_{t+1}} + \beta(1+r) \frac{\partial \mathcal{W}_t}{\partial C_t} \left\{ p \frac{\partial V(A_{t+1},S_{t+1}^{-1},E_{t+1})}{\partial A_{t+1}} + (1-p) \frac{\partial V(A_{t+1},S_{t+1}^0,E_{t+1})}{\partial A_{t+1}} \right\} = 0
\] (7.4)

The addition of human capital to the model changes the condition for the optimal time spent in legitimate income producing activities.

To obtain the Euler equations, we begin by substituting (7.1) into (7.2).
\[
\frac{\partial V(A_t, S_t, E_t)}{\partial L_t} = -U_2(t) + U_1(t) \frac{\partial W_L}{\partial L_t} + \beta K(1 - p) \frac{\partial V(A_{t+1}, S_{t+1}, E_{t+1})}{\partial S_{t+1}} \\
+ \beta \mu \left\{ p \frac{\partial V(A_{t+1}, S_{t+1}^1, E_{t+1})}{\partial E_{t+1}} + (1 - p) \frac{\partial V(A_{t+1}, S_{t+1}, E_{t+1})}{\partial E_{t+1}} \right\} = 0
\]  

(7.5)

We substitute (7.1) and (7.3) into (7.4) to obtain the Euler equation for \( C_t' \).

\[
U_1(t) \frac{\partial W_c(C_t')}{\partial C_t'} - U_3(t) = 0
\]  

(7.6)

To express equation (7.1) in terms of known functions, use the envelope theorem:

\[
\frac{\partial V(A_t, S_t, E_t)}{\partial A_t} = \beta(1 + r) \left\{ p \frac{\partial V(A_{t+1}, S_{t+1}^1, E_{t+1})}{\partial A_{t+1}} + (1 - p) \frac{\partial V(A_{t+1}, S_{t+1}, E_{t+1})}{\partial A_{t+1}} \right\}
\]  

(7.7)

The steps followed in the previous section are used to arrive at the Euler equation for \( X_t \).

\[
U_1(t) - \beta(1 + r) \{ pU_1'(t + 1) + (1 - p) U_1'(t + 1) \} = 0
\]

However, Euler equations cannot be obtained for the optimal choice of \( L_t \) and \( C_t' \), since we cannot solve for the partial derivatives of the value function in period \( t+1 \). This issue is pursued in terms of its implications for estimation in Section 7.3.
7.2 A Dynamic Model of Crime with Endogenous Probability of Arrest

We now return to the basic dynamic model of crime developed in Chapter 3 and relax the assumption of an exogenous capture probability. At each point in time, an individual's probability of arrest is assumed to depend positively on the amount of resources devoted to crime.

The individuals dynamic programming problem at time $t$ becomes:

$$V(A_t, S_t) = \max_{x_t, t, l^c, l^i} U(X_t, l_t, C_t^c, S_t) + \beta \left\{ p(C_t) V(A_{t+1}, S_{t+1}^1) + (1 - p(C_t)) V(A_{t+1}, S_{t+1}^0) \right\}$$

Subject to:

1) $T = l_t + L_t + C_t$

2) $C_t = C_t^c + C_t^i$

3) $A_{t+1} = (1 + r) \left( A_t + W_L(L_t, S_t) + W_C(C_t^i - X_t) \right)$

4) $S_{t+1}^1 = (1 - \sigma - \alpha C_t) S_t$ \hspace{1cm} if caught
   $S_{t+1}^0 = (1 - \sigma) S_t + \gamma L_t$ \hspace{1cm} if not caught

By substituting (1) in for $l_t$, we eliminate $l_t$ as a choice variable. The first order conditions with respect to $X_t, L_t, C_t^i$ and $C_t^c$ are:

$$\frac{\partial V(A_t, S_t)}{\partial X_t} = U_t(t) - \beta T \left\{ p(C_t) \frac{\partial V(A_{t+1}, S_{t+1}^1)}{\partial A_{t+1}} \right. \right. \left. \left. + (1-p(C_t)) \frac{\partial V(A_{t+1}, S_{t+1}^0)}{\partial A_{t+1}} \right\} = 0 \hspace{1cm} (7.8)$$
\[
\frac{\partial V(A_t, S_t)}{\partial L_t} = -U_2(t) + \beta \gamma (1 - p(C_t)) \frac{\partial V(A_{t+1}, S_{t+1}^0)}{\partial S_{t+1}}
+ \beta (1 + r) \frac{\partial W_c}{\partial L_t} + \left\{ p(C_t) \frac{\partial V(A_{t+1}, S_{t+1})}{\partial A_{t+1}} + (1 - p(C_t)) \frac{\partial V(A_{t+1}, S_{t+1}^0)}{\partial A_{t+1}} \right\} = 0
\]

\[
\frac{\partial V(A_t, S_t)}{\partial C_t} = U_2(t) - U_2(t) + \beta \frac{\partial p(C_t)}{\partial C_t} \left\{ V(S_{t+1}^0, A_{t+1}) - V(S_{t+1}^0, A_{t+1}) \right\}
- \beta \alpha S_t p(C_t) \frac{\partial V(A_{t+1}, S_{t+1}^0)}{\partial S_{t+1}} = 0
\]

\[
\frac{\partial V(A_t, S_t)}{\partial C'_t} = -U_2(t) + \beta \frac{\partial p(C_t)}{\partial C'_t} \left\{ V(S_{t+1}^0, A_{t+1}) - V(S_{t+1}^0, A_{t+1}) \right\}
- \beta (1 + r) \frac{\partial W_c}{\partial C'_t} \left\{ p(C_t) \frac{\partial V(A_{t+1}, S_{t+1})}{\partial S_{t+1}} + (1 - p(C_t)) \frac{\partial V(A_{t+1}, S_{t+1}^0)}{\partial S_{t+1}} \right\}
- \beta \alpha S_t p(C_t) \frac{\partial V(A_{t+1}, S_{t+1}^0)}{\partial S_{t+1}} = 0
\]

The first order conditions with respect to time in crime now contain terms in the level of the value function at \( t+1 \).

To obtain Euler equations, begin by substituting (7.8) into (7.9).

\[
\frac{\partial V(A_t, S_t)}{\partial L_t} = -U_2(t) + U_1(t) \frac{\partial W_c(L_t, S_t)}{\partial L_t} + \beta \gamma (1 - p(C_t)) \frac{\partial V(A_{t+1}, S_{t+1}^0)}{\partial S_{t+1}} = 0
\]

Substitute (7.10) and (7.8) into (7.11) to obtain the Euler equation for \( C'_t \).
\[ U_1(t) \frac{\partial W_C(C'_t)}{\partial C'_t} - U_3(t) = 0 \quad (7.13) \]

From the envelope theorem:

\[ \frac{\partial V(A_t, S_t)}{\partial A_t} = \beta(1 + r) \left\{ p(C_t) \frac{\partial V(A_{t+1}, S_{t+1}^1)}{\partial A_{t+1}} + (1 - p(C_t)) \frac{\partial V(A_{t+1}, S_{t+1}^0)}{\partial A_{t+1}} \right\} \quad (7.14) \]

Substituting equation (7.8) into (7.14):

\[ \frac{\partial V(A_t, S_t)}{\partial A_t} = U_1(t) \quad (7.15) \]

Updating (7.15) by one period:

\[ \frac{\partial V(A_{t+1}, S_{t+1})}{\partial A_{t+1}} = U_1(t+1) \quad (7.16) \]

Evaluating at \( S_{t+1}^1 \) and \( S_{t+1}^0 \) we obtain (7.17) and (7.18).

\[ U_1^1(t+1) = \frac{\partial V(A_{t+1}, S_{t+1}^1)}{\partial A_{t+1}} \quad (7.17) \]

\[ U_1^0(t+1) = \frac{\partial V(A_{t+1}, S_{t+1}^0)}{\partial A_{t+1}} \quad (7.18) \]

Substituting equations (7.17) and (7.18) into equation (7.8) we obtain the Euler equation for \( X_t \).

\[ U_1(t) - \beta(1 + r) \left\{ p(C_t) U_1^1(t+1) + (1 - p(C_t)) U_1^0(t+1) \right\} = 0 \quad (7.19) \]
Using the Envelope theorem, again, we obtain:

$$\frac{\partial V(A_t, S_t)}{\partial S_t} = U_4(t + l) + \beta \left\{ (1 - \delta - \alpha C_t) p(C_t) \frac{\partial V(A_{t+1}, S_{t+1})}{\partial S_{t+1}} 
+ (1 - \delta)(1 - p(C_t)) \frac{\partial V(A_{t+1}, S_{t+1})}{\partial S_{t+1}} \right\}$$  \hspace{1cm} (7.20)

Substituting equations (7.10) and (7.12) and into equation (7.20), we have:

$$\frac{\partial V(A_t, S_t)}{\partial S_t} = U_4(t) + \frac{(1 - \delta)}{\gamma} \left\{ U_2(t) - U_1(t) \frac{\partial W_L(L_t, S_t)}{\partial S_t} \right\}$$

$$+ \frac{(1 - \delta - \alpha C_t)}{\alpha S_t} \left\{ U_3(t) - U_2(t) + \beta \frac{p(C_t)}{C_t} \left[ V_1(A_{t+1}, S_{t+1}) - V(A_{t+1}, S_{t+1}) \right] \right\}$$  \hspace{1cm} (7.21)

We are unable to write equation (21) in terms of this period and next period variables and known functions. Therefore, we cannot solve for the terms involving partial derivatives of the value function in the first order conditions for $L_t$ and $C_t^C$. Estimation will be complicated by the presence of these terms. This issue is addressed in the following section.

### 7.3 Implications of the Extended Models for Estimation

When the basic model is extended, either by introducing human capital or allowing the probability of arrest to depend on an individual's actions, we can no longer obtain closed form solutions for the optimal choice of time in the labor market or time in crime. In order to obtain estimates of structural parameters, we propose implementing an iterative
process which makes use of both numerical methods of solution and the Simulated
Method of Moments estimator.

In the case of the extended models, the presence of terms involving the value function or
its derivatives further complicates estimation. This becomes an issue because the value
function is not specified completely by parameterizing the utility and wage functions.
There are several ways this can be addressed. Successive approximation, also referred to
as value function iteration, starts with an arbitrary guess from within a family of functions,
(e.g., polynomials) for a solution to Bellman's equation. Given this initial guess and
parameter values for the utility and wage functions, a grid search over a finite partition of
the state space is used to obtain the optimal values of the choice variables. The Bellman
operator is then iterated for this set of solutions to the first order conditions. Using the
contraction mapping theorem, this algorithm will find a fixed point which can be made
arbitrarily close to the solution to the original problem. (In the original problem, the value
function is continuous, whereas the grid search is carried out by evaluating a discrete
functional approximation to the value function). An initial guess of the Bellman equation
equal to zero is equivalent to solving an approximate finite-horizon problem by backward
induction. An alternative approach to approximating the value function is to use
orthogonal polynomials (Judd, 1994, 1995). In this method, one considers a finitely
parameterizable collection of functions, where the functional form could be a linear
combination of orthogonal polynomials. The value function $V(x)$ is approximated by
$\hat{V}(X; \alpha)$ where $\alpha$ is a vector of coefficients. Once the basic functional forms are
determined, e.g. a linear combination of orthogonal polynomials, splines, or neural networks, one focuses on finding the coefficients $\alpha$ so that the function $\hat{V}(X; \alpha)$ approximately satisfies the Bellman equation by choosing a residual function to estimate coefficients. For more detail on these procedures see Judd and Solnick (1994) and Judd (1995).

Once an estimate for the value function is obtained, it is substituted into the first order conditions and the Simulated Method of Moments used to obtain structural parameter estimates. The new set of parameter estimates is used to update the estimate of the value function. Iteration on parameters and value function estimates continues in this fashion until (the criteria for) convergence is reached.

7.4 Summary

This chapter demonstrates that our basic model can be easily extended to produce richer models of the decision to participation in crime. The two modifications we consider are incorporating human capital and allowing an endogenous probability of arrest. While adopting either extension poses no problem at a theoretical level, it does complicate estimation. Either modification results in conditions for optimality which include terms involving the value function or its derivatives. This becomes an issue since the value function is not completely parameterized by specifying the utility and wage functions. To obtain estimates of structural parameters, we propose an iterative technique which nests a
numerical method of solution within a Simulated Method of Moments estimator. The implementation of this technique will be pursued in future work.
CHAPTER 8

CONCLUSION

This research takes a structural approach to examining the decision to participate in crime within a life-cycle setting. Our work differs from previous studies of crime in that it develops and implements a dynamic model of individual choice under uncertainty. We extend the conventional time allocation model to a dynamic setting by incorporating a social capital representation of social control theory. In doing so, we generate a dynamic model where individual’s anticipate future consequences of their actions, while placing the social control theory of participation in crime in a testable framework.

Social control theory posits that as an individual ages, his ties to legitimate society strengthen. These social ties create interdependent systems of obligation and restraint that impose significant costs for translating criminal propensities into crime, making the occurrence of crime less likely. The process by which an individual becomes more closely bonded to society is represented in our formulation by the individual accumulating social capital. Within this framework, the social control theory hypothesis predicts that social capital becomes more important to individuals as they age and this is reflected in lower participation in crime.
In our model, social capital is hypothesized to influence individual's behavior in three distinct ways. First, by penalizing individuals for deviant behavior; in breaking the law, an agent risks a reduction in his social capital since an arrest entails a social sanction. The sanction is assumed to be increasing in social capital. This specification is consistent with the basic premise of social control theory: *ceteris paribus*, crime is more costly (and therefore less likely) for those who are tightly bonded to their community. Second, through wages; social capital includes the networks that are built up at work and in the community. These networks serve to disseminate information about opportunities for advancement in the legitimate sector. We capture this effect by allowing the accumulation of social capital to raise market wages. Third, social capital affects preferences. In part, social capital represents reputation and social acceptance. This has a utility value to the individual. This formulation of social control theory generates four testable hypotheses: Social capital is reduced when an individual is caught engaging in crime; social capital raises market wages; social capital is significant in the preference structure; and social capital becomes increasingly important as an individual ages.

Our results provide strong empirical support for all four of the predictions of social control theory. Principal component analysis confirms the social sanction hypothesis by generating a negative weight on time spent in crime (interacted with social capital stock) for individuals who were arrested. Market wages are found to be positively related to social capital. Moreover, the magnitude of this effect is found to be the same as the earnings premium associated with investment in human capital. Social capital contributes
significantly to the welfare of our sample of young men. Also, we find evidence that their preference structure is nonseparable in consumption, leisure, and social capital. We find, consistent with social control theory, the marginal utility of social capital increases over the sample period. Moreover, an individual’s welfare becomes more responsive to changes in social capital, relative to consumption or leisure, as he ages.

The social control theory of crime postulates that increasing bonds to legitimate society impose increasing costs of engaging in crime, making the occurrence of crime less likely as an individual ages. This is precisely the pattern of behavior observed when we compare the age-crime profile for our sample with the (average) marginal utility of social capital. In particular, we find that the late teens to early twenties is a crucial time in the life-cycle for forming social capital and making the transition from youth culture to legitimate adult society. Our results are consistent with a scenario in which individuals who have not made the transition to legitimate culture by twenty-one may never do so. Further exploration of this issue reveals that social capital is in fact a ‘bad’ for individuals embedded in a criminal culture. Nonetheless, these individual’s attempt to transition to legitimate society. The failure of the marginal value of social capital to become positive, coupled with the dramatic decrease in its value after age twenty-one, signals the inability of these people to make that transition and their consequent absorption into criminal culture.
Our findings not only provide evidence of the importance of social capital in the decision to participate in crime. They indicate that a low social capital stock inherited from childhood puts an individual at greater risk of becoming a criminal in adulthood.

Consistent with this result, Greenwood et al. (1996) has found that parent training and graduation incentives schemes are effective methods for reducing crime. According to a social capital perspective, these programs work through increasing social capital of the family. Parental training programs are designed to facilitate parent-child relations in the face of aggressive children, who have begun ‘acting-out’ in school. High school graduation programs work to increase social capital of the family by providing ties to the legitimate community outside the home, thereby preventing absorption into deviant youth culture, and providing information about legitimate opportunities.

Also evident from our results is the dynamic nature of the process of absorption into legitimate culture, as represented by social capital accumulation. The late teenage years to early twenties is a crucial time for making the transition to legitimate culture, even for those most disadvantaged in terms of family social capital stock. This suggests a role for preventative policies beyond the childhood years.

The significance of our research is that it uses social capital as the mechanism by which nondeviant behavior is produced. By definition, crime is behavior deemed deviant by society. It seems appropriate then, to integrate this perspective into the economic model of crime. In doing so, we have developed an economic theory of the production of
nondeviant behavior, where social capital is an input to production. This theory is analogous to consumer theory, where consumption goods and leisure time are inputs to the production of utility, or producer theory, where labor and capital stock are inputs to the production of goods and services. Moreover, adopting this integrated approach provides us with a perspective to view the way preventative government policy may influence potential deviant behavior. Our theory implies that policies which increase the social capital stock of individuals will increase the production of nondeviant behavior. Combined with the existing research on deterrence, we are now armed with both the proverbial carrot and stick in terms of policy instruments for addressing the important economic issue of crime.
REFERENCES


Bearse, P., “On the Age-Arrest Profile”, mimeo, University of Virginia


Brown, B. W., (1993) "Optimal Endogenous Instrumental Variables Estimation in Nonlinear Systems", mimeo, Department of Economics, Rice University, Houston, TX.


Needles, K., (1993), "Go Directly To Jail and Do Not Collect?: A Long Term Study of Recidivism and Employment Patterns Among Prison Releasees", mimeo, Princeton University


Sickles, R. C. and Yazbeck (1996), A. "On the Dynamics of Demand for Leisure and the Production of Health", mimeo, Department of Economics, Rice University, Houston, TX.


APPENDIX 1

A HUMAN CAPITAL MODEL OF CRIME

The variables contained in this model are defined in Chapter 3 and Chapter 7, with the exception of \( F(C_t) \), which is the monetary equivalent of the punishment incurred in the event of apprehension.

The representative agent's dynamic programming problem at time \( t \) for the human capital model of crime is

\[
V(A_t, E_t) = \max_{X_t, L_t, C_t} U(X_t, \ell_t, C_t') + \beta \left( pV(A_{t+1}, E_{t+1}) + (1-p)V(A_{t+1}^0, E_{t+1}) \right)
\]

Subject to:

1) \( T = \ell + L + C \)

2) \( C_t = C_t' + C_t'' \)

3) \( E_t = (1-\eta)E_t + \mu L_t \)

4) \( A_{t+1} = (1+r)(A_t + W_L(L_t, E_t) + W_C(C_t') - F(C_t) - X_t) \)
   \( A_{t+1}^0 = (1+r)(A_t + W_L(L_t, E_t) + W_C(C_t') - X_t) \)

First Order Conditions:

\[
\frac{\partial V(A_t, E_t)}{\partial X_t} = U_t(t) - \beta(1+r) \left\{ p \frac{\partial V(A_{t+1}^1, E_{t+1})}{\partial A_{t+1}} + (1-p) \frac{\partial V(A_{t+1}^0, E_{t+1})}{\partial A_{t+1}} \right\} = 0 \tag{A1.1}
\]

\[
\frac{\partial V(A_t, E_t)}{\partial L_t} = -U_2(t) + \beta \mu \left\{ p \frac{\partial V(A_{t+1}^1, E_{t+1})}{\partial E_{t+1}} + (1-p) \frac{\partial V(A_{t+1}^0, E_{t+1})}{\partial A_{t+1}} \right\} \\
+ \beta(1+r) \frac{\partial V(L_t, E_t)}{\partial L_t} \left\{ p \frac{\partial V(A_{t+1}^1, E_{t+1})}{\partial A_{t+1}} + (1-p) \frac{\partial V(A_{t+1}^0, E_{t+1})}{\partial A_{t+1}} \right\} = 0 \tag{A1.2}
\]
\[
\frac{\partial V(A_t, E_t)}{\partial C_i} = U_3(t) - U_2(t) - \beta(1+r)p \frac{\partial F(C_t)}{\partial C_t} \frac{\partial V(A_{t+1}^1, E_{t+1})}{\partial A_{t+1}} = 0 \tag{A1.3}
\]

\[
\frac{\partial V(A_t, E_t)}{\partial C_i} = -U_2(t) - \beta(1+r)p \frac{\partial F(C_t)}{\partial C_t} \frac{\partial V(A_{t+1}^1, E_{t+1})}{\partial A_{t+1}} \\
+ \beta(1+r)p \frac{\partial W(C_i)}{\partial C_i} \left[ \frac{\partial V(A_{t+1}^1, E_{t+1})}{\partial A_{t+1}} + (1-p) \frac{\partial V(A_{t+1}^0, E_{t+1})}{\partial A_{t+1}} \right] = 0 \tag{A1.4}
\]

From the envelope theorem:

\[
\frac{\partial V(A_t, E_t)}{\partial A_t} = \beta(1+r) \left[ p \frac{\partial V(A_{t+1}^1, E_{t+1})}{\partial A_{t+1}} + (1-p) \frac{\partial V(A_{t+1}^0, E_{t+1})}{\partial A_{t+1}} \right] \tag{A1.5}
\]

Substitute (A1.1) into (A1.5):

\[
\frac{\partial V(A_t, E_t)}{\partial A_t} = U_1(t) \tag{A1.6}
\]

Updating (A1.6) one period:

\[
\frac{\partial V(A_{t+1}, E_{t+1})}{\partial A_{t+1}^1} = U_1(t+1) \tag{A1.7}
\]

Define:

\[
\frac{\partial V(A_{t+1}^1, E_{t+1})}{\partial A_{t+1}} = U_1^1(t+1) \tag{A1.8}
\]
\[ \frac{\partial V(A_{t+1}^0, E_{t+1})}{\partial A_{t+1}} = U_t^0(t + 1) \] (A1.9)

Substitute (A1.8) and (A1.9) into (A1.1) to get the Euler equation for \( X_t \).

\[ U_1(t) - \beta(1+r)\left\{ pU_1^1(t+1) + (1-p)U_t^0(t+1) \right\} = 0 \] (A1.10)

Substitute (A1.8) into (A1.3) to get the Euler equation for \( C_t^C \)

\[ U_3(t) - U_2(t) - \beta(1+r)p \frac{\partial F(C_t)}{\partial C_t} U_1^1(t+1) = 0 \] (A1.11)

Substitute (A1.1) and (A1.3) into (A1.4) to get the Euler equation for \( C_t^I \)

\[ U_1(t) \frac{\partial W_C(C_t^I)}{\partial C_t} - U_3(t) = 0 \] (A1.12)

Substitute (A1.1) into (A1.2) to obtain (A1.13)

\[ -U_2(t) + U_1(t) \frac{\partial W_L(L_t, E_t)}{\partial L_t} + \mu \beta \left\{ p \frac{\partial V(A_{t+1}^1, E_{t+1})}{\partial E_{t+1}} + (1-p) \frac{\partial V(A_{t+1}^0, E_{t+1})}{\partial E_{t+1}} \right\} = 0 \] (A1.13)

Using the envelope theorem

\[ \frac{\partial V(A_t, E_t)}{\partial E_t} = \beta(1-\eta) \left\{ p \frac{\partial V(A_{t+1}^1, E_{t+1})}{\partial E_{t+1}} + (1-p) \frac{\partial V(A_{t+1}^0, E_{t+1})}{\partial E_{t+1}} \right\} 
+ \beta(1+r) \frac{\partial W_L(L_t, E_t)}{\partial E_t} \left\{ p \frac{\partial V(A_{t+1}^1, E_{t+1})}{\partial A_{t+1}} + (1-p) \frac{\partial V(A_{t+1}^0, E_{t+1})}{\partial A_{t+1}} \right\} \] (A1.14)

Substituting (A1.1) and (A1.13) into (A1.14)
\[
\frac{\partial V(A_t, E_t)}{\partial E_t} = \frac{(1-\eta)}{\mu} \left\{ U_2(t) - U_1(t) \frac{\partial W_k(L_z, E_t)}{\partial L_z} \right\} + U_1(t) \frac{\partial W_k(L_z, E_t)}{\partial L_z} \tag{A1.15}
\]

Updating 1 period:

\[
\frac{\partial V(A_{t+1}, E_{t+1})}{\partial E_{t+1}} = \frac{(1-\eta)}{\mu} \left\{ U_2(t+1) - U_1(t+1) \frac{\partial W_k(L_{t+1}, E_{t+1})}{\partial L_{t+1}} \right\} + U_1(t+1) \frac{\partial W_k(L_{t+1}, E_{t+1})}{\partial L_{t+1}} \tag{A1.16}
\]

Evaluating (A1.16) at \(A_{t+1}^I\) and \(A_{t+1}^O\) respectively we have:

\[
\frac{\partial V(A_{t+1}^1, E_{t+1})}{\partial E_{t+1}} = \frac{(1-\eta)}{\mu} \left\{ U_2^1(t+1) - U_1^1(t+1) \frac{\partial W_k(L_{t+1}^1, E_{t+1})}{\partial L_{t+1}} \right\} + U_1^1(t+1) \frac{\partial W_k(L_{t+1}^1, E_{t+1})}{\partial L_{t+1}} \tag{A1.17}
\]

\[
\frac{\partial V(A_{t+1}^0, E_{t+1})}{\partial E_{t+1}} = \frac{(1-\eta)}{\mu} \left\{ U_2^0(t+1) - U_1^0(t+1) \frac{\partial W_k(L_{t+1}^0, E_{t+1})}{\partial L_{t+1}} \right\} + U_1^0(t+1) \frac{\partial W_k(L_{t+1}^0, E_{t+1})}{\partial L_{t+1}} \tag{A1.18}
\]

Substitute (A1.18) into (A1.13), We obtain the last Euler equation for \(L_t\).
\[
\beta (1 - \eta) \left\{ U_2(t+1) - U_1(t+1) \frac{\partial W_{L}(L_{t+1}, E_{t+1})}{\partial L_{t+1}} \right\} + \mu U_1(t+1) \frac{\partial W_{L}(L_{t+1}, E_{t+1})}{\partial L_{t+1}} \\
+ \beta (1 - p) \left\{ (1 - \eta) \left\{ U_2^0(t+1) - U_1^0(t+1) \frac{\partial W_{L}(L_{t+1}^0, E_{t+1})}{L_{t+1}} \right\} \right\} \\
+ \mu U_1^0(t+1) \frac{\partial W_{L}(L_{t+1}^0, E_{t+1})}{\partial L_{t+1}} \right\} - U_2(t) + U_1(t) \frac{\partial W_{L}(L_t, E_t)}{\partial L_t} = 0
\]  

(A1.19)

The Euler equations are:

\[X_t: U_1(t) - \beta (1 + r) \{ p U_1^0(t+1) + (1 - p) U_1(t+1) \} = 0\]

\[L_t: \beta (1 - \eta) \left\{ U_2(t+1) - U_1(t+1) \frac{\partial W_{L}(L_{t+1}, E_{t+1})}{\partial L_{t+1}} \right\} + \mu U_1(t+1) \frac{\partial W_{L}(L_{t+1}, E_{t+1})}{\partial L_{t+1}} \\
+ \beta (1 - p) \left\{ (1 - \eta) \left\{ U_2^0(t+1) - U_1^0(t+1) \frac{\partial W_{L}(L_{t+1}^0, E_{t+1})}{L_{t+1}} \right\} \right\} + \mu U_1^0(t+1) \frac{\partial W_{L}(L_{t+1}^0, E_{t+1})}{\partial L_{t+1}} \right\} - U_2(t) + U_1(t) \frac{\partial W_{L}(L_t, E_t)}{\partial L_t} = 0\]

\[C_t^f: U_3(t) - U_2(t) - \beta (1 + r) \frac{\partial F(C_t)}{\partial C_t} p U_1^0(t+1) = 0\]

\[C_t^l: U_1(t) \frac{\partial W_{L}(C_t)}{\partial C_t} - U_3(t) = 0\]
APPENDIX 2

THE SELLIN-WOLFGANG SERIOUSNESS SCORING SCALE

In order that we may analyze crime, and not have to worry about aggregating different offenses, the Sellin Wolfgang seriousness scoring scale is used. The appeal of this approach is that it uses the effects of the crimes rather than the specific legal labels attached to them to index the severity or gravity of criminal behavior. The seriousness scores of offense gravity consists of three parts. The first part is constructed utilizing events which involve violations of the criminal law that inflict bodily harm on one or more victims and/or cause property loss by theft or damage or destruction. In order to score criminal events for this part of the scale, the following rap-sheet information included in the adult offense file was used:

1. The number of victims who, during the event receive minor bodily injuries, or are treated and discharged, hospitalized, or killed.

2. The number of victims of acts of forcible sexual intercourse.

3. The presence of physical or verbal intimidation or intimidation by a dangerous weapon.

4. The number of premises forcibly entered.

5. The number of motor vehicles stolen and whether the vehicle was or was not recovered.

The following table lists the seriousness scoring components and the weights devised by Wolfgang and Sellin used for the first part of the seriousness score. The score for an event is computed as follows. The weights are multiplied by the number of victims who were affected by the various scores and summed.
Table A2.1  
*Seriousness Scoring Components and Weights*

<table>
<thead>
<tr>
<th>Component</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Physical injury</td>
<td></td>
</tr>
<tr>
<td>a. minor harm</td>
<td>1.5</td>
</tr>
<tr>
<td>b. treated and discharged</td>
<td>8.5</td>
</tr>
<tr>
<td>c. hospitalization</td>
<td>12.0</td>
</tr>
<tr>
<td>d. fatal</td>
<td>35.7</td>
</tr>
<tr>
<td>2. Forcible sex acts</td>
<td>26.0</td>
</tr>
<tr>
<td>3. Intimidation</td>
<td></td>
</tr>
<tr>
<td>a. verbal or physical</td>
<td>4.9</td>
</tr>
<tr>
<td>b. by weapon</td>
<td>5.6</td>
</tr>
<tr>
<td>4. Premises forcibly entered</td>
<td>1.5</td>
</tr>
<tr>
<td>5. Motor Vehicles stolen</td>
<td></td>
</tr>
<tr>
<td>a. recovered</td>
<td>4.5</td>
</tr>
<tr>
<td>b. unrecovered</td>
<td>8.1</td>
</tr>
</tbody>
</table>

The adult offense file also has a second and third part to the seriousness score, which focuses on the seriousness of crimes that have no 'victims', nor involve theft or property damage. The final seriousness score used in the following analysis is the aggregate of the three parts of the seriousness scores.
APPENDIX 3

DEFINITION OF VARIABLES

*Model Variables*

\[ L_t \]
hours worked in labor market per year

\[ C_t \]
hours worked in crime per year

\[ I_t \]
hours of leisure per year

\[ X_t \]
composite consumption good

\[ S_t \]
stock of social capital

\[ W_L \]
annual income from labor market

\[ W_C \]
annual income from crime

*Variables used to Create the Initial Level of Social Capital*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAD</td>
<td>dummy = 1 if father present in childhood home</td>
</tr>
<tr>
<td>DA1</td>
<td>dummy = 1 if father arrested during childhood</td>
</tr>
<tr>
<td>SIBS</td>
<td>number of siblings when growing up</td>
</tr>
<tr>
<td>WHITE</td>
<td>dummy = 1 if race is white</td>
</tr>
<tr>
<td>SES</td>
<td>dummy = 1 if socioeconomic status is high</td>
</tr>
<tr>
<td>GANGL18</td>
<td>dummy = 1 if individual was in a gang during childhood</td>
</tr>
<tr>
<td>MATEBOOK</td>
<td>the number of closest 3 friends during high school picked up by the police</td>
</tr>
<tr>
<td>ARCON</td>
<td>proportion of police contacts as a juvenile that result in arrest</td>
</tr>
</tbody>
</table>

*Variables used in Social Capital Accumulation and Tobit Models*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>BEGM</td>
<td>dummy=1 if begin marriage that year</td>
</tr>
<tr>
<td>CHJ</td>
<td>dummy=1 if leave a job and start a new one that year</td>
</tr>
<tr>
<td>ED</td>
<td>dummy=1 if level of educate is at least a high school diploma</td>
</tr>
<tr>
<td>SCHOOL</td>
<td>dummy=1 if education not completed</td>
</tr>
<tr>
<td>MARRY</td>
<td>dummy=1 if individual is married</td>
</tr>
<tr>
<td>NOMUM</td>
<td>dummy=1 if mother not present when growing up</td>
</tr>
<tr>
<td>DEFACTO</td>
<td>dummy=1 if in a common law marriage</td>
</tr>
<tr>
<td>MOVE</td>
<td>dummy=1 if move out of parents home</td>
</tr>
<tr>
<td>NUMKIDS</td>
<td>number of children the individual has</td>
</tr>
<tr>
<td>ARREST</td>
<td>dummy=1 if arrested that year</td>
</tr>
<tr>
<td>AARREST</td>
<td>dummy=1 if arrested for an income crime that year</td>
</tr>
<tr>
<td>ED2</td>
<td>dummy=1 if have a high school diploma but not a college degree</td>
</tr>
<tr>
<td>ED3</td>
<td>dummy=1 if a college graduate</td>
</tr>
</tbody>
</table>
APPENDIX 4

DESCRIPTIVE STATISTICS

Model Variables

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L_t$</td>
<td>1,566.22</td>
<td>897.40</td>
</tr>
<tr>
<td>$C_t$</td>
<td>75.24</td>
<td>197.90</td>
</tr>
<tr>
<td>$I_t$</td>
<td>4,182.54</td>
<td>891.56</td>
</tr>
<tr>
<td>$X_t$</td>
<td>125.29</td>
<td>86.01</td>
</tr>
<tr>
<td>$S_t$</td>
<td>96.56</td>
<td>19.55</td>
</tr>
<tr>
<td>$W_L$</td>
<td>102.31</td>
<td>94.25</td>
</tr>
<tr>
<td>$W_C$</td>
<td>3.63</td>
<td>16.83</td>
</tr>
</tbody>
</table>

Variables used to Create the Initial Level of Social Capital

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAD</td>
<td>0.82</td>
<td>0.39</td>
</tr>
<tr>
<td>DA1</td>
<td>0.11</td>
<td>0.31</td>
</tr>
<tr>
<td>SIBS</td>
<td>3.27</td>
<td>2.17</td>
</tr>
<tr>
<td>WHITE</td>
<td>0.56</td>
<td>0.50</td>
</tr>
<tr>
<td>SES</td>
<td>0.54</td>
<td>0.50</td>
</tr>
<tr>
<td>GANGLT18</td>
<td>0.29</td>
<td>0.45</td>
</tr>
<tr>
<td>MATEBOOK</td>
<td>1.43</td>
<td>1.36</td>
</tr>
<tr>
<td>ARCON</td>
<td>0.35</td>
<td>0.39</td>
</tr>
</tbody>
</table>

Variables used in Social Capital Accumulation and Tobit Models

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>BEGM</td>
<td>0.05</td>
<td>0.23</td>
</tr>
<tr>
<td>CHJ</td>
<td>0.10</td>
<td>0.30</td>
</tr>
<tr>
<td>ED</td>
<td>0.66</td>
<td>0.47</td>
</tr>
<tr>
<td>SCHOOL</td>
<td>0.15</td>
<td>0.36</td>
</tr>
<tr>
<td>MARRY</td>
<td>0.17</td>
<td>0.38</td>
</tr>
<tr>
<td>NOMUM</td>
<td>0.02</td>
<td>0.15</td>
</tr>
<tr>
<td>DEFACTO</td>
<td>0.11</td>
<td>0.31</td>
</tr>
<tr>
<td>MOVE</td>
<td>0.07</td>
<td>0.26</td>
</tr>
<tr>
<td>NUMKIDS</td>
<td>1.30</td>
<td>1.35</td>
</tr>
<tr>
<td>ARREST</td>
<td>0.10</td>
<td>0.30</td>
</tr>
<tr>
<td>AARREST</td>
<td>0.06</td>
<td>0.24</td>
</tr>
<tr>
<td>ED2</td>
<td>0.60</td>
<td>0.49</td>
</tr>
<tr>
<td>ED3</td>
<td>0.06</td>
<td>0.24</td>
</tr>
</tbody>
</table>
APPENDIX 5

PRINCIPAL COMPONENTS

The purpose of principal component analysis is to reduce the dimensionality of a data set containing a large number of interrelated variables while maintaining as much information as possible. This reduction is achieved by defining a new set of orthogonal variables, principal components, which are linear combinations of the original variables. The principal components are ordered so that the first principal component accounts for more of the variation in all of the original variables than the second, and so on. Computation of the principal components reduces to the solution of an eigenvalue-eigenvector problem for the covariance (or correlation) matrix of the data.

Suppose we have $n$ observations on the vector of continuous random variables, $X = (X_1, X_2, \ldots, X_p)$. Let $X$ have zero mean and covariance matrix $E(XX') = \Sigma$.

The objective of principal components is to form $m < p$ new variables, $Z = XA$, which account for as much of the variation in $X$ as possible. So the method of principal components seeks the orthogonal weighting matrix $A$, which maximizes:

$$V(Z) = V(XA) = E(A'XXA) = A' \Sigma A.$$

To obtain a unique solution to this problem, a normalization for $A$ must be chosen. One such normalization is $A' A = I$. Imposing this constraint, we can write the problem of finding the set of weights which maximize the variance of the principal components as:

$$\Phi = \max_A A' \Sigma A - \lambda (A' A - I)$$  \hspace{1cm} (A4.1)

where $\lambda$ is a vector of Lagrange multipliers. Differentiating with respect to $A$, we obtain the first order condition

$$\frac{\partial \Phi}{\partial A} = 2 \Sigma A - 2 \lambda A = 0$$  \hspace{1cm} (A4.2)
which implies that

\[(\Sigma - \lambda I)A = 0.\] \hspace{1cm} (A4.3)

The \(p \times 1\) vector, \(\lambda\), are the roots, or eigenvalues of the determinant polynomial

\[|\Sigma - \lambda I| = 0.\] \hspace{1cm} (A4.4)

Once the eigenvalues are known, the matrix of eigenvectors, \(A\), can be found using equation (A4.3). The \(k\)th principal component is defined as:

\[Z_k = \sum_{i=1}^{p} \alpha_{ki} X_i\]

where \(\alpha_{k}\) is the \(k\)th column of \(A\), which is the eigenvector corresponding to the \(k\)th eigenvalue. Since the eigenvectors, \(\alpha_{k}\), are orthogonal, the principal components, \(z_k\), are uncorrelated random variables with \(V(z_k) = \lambda_k\) (Basilevsky, 1994).
APPENDIX 6

COMPUTER PROGRAM FOR SIMULATING DATA

/***************************************************************************/
THIS PROGRAM SIMULATES DATA FOR TIME IN INCOME PRODUCING CRIME IN THE STATE
OF THE WORLD NOT ARRESTED
/***************************************************************************/

BINNING UP SOCIAL CAPITAL
***************************************************************************/

DATA STEP5A; SET ASK14.DAT;
KEEP INTNO YR STPLS10 CITPLS10 STCAT ARREST CIT CITPLS11;
ST=ST/100; STPLS11=STPLS11/100; STPLS10=STPLS10/100;
ST=ROUND(ST,1); STPLS11=ROUND(STPLS11,1); STPLS10=ROUND(STPLS10,1);
IF STPLS10<=79 THEN STCAT=1; ELSE IF 80<=STPLS10<=93 THEN STCAT=2;
ELSE IF 94<=STPLS10<=102 THEN STCAT=3; ELSE IF 103<=STPLS10<=113
THEN STCAT=4; ELSE IF STPLS10 >= 114 THEN STCAT=5;
PROC SORT; BY STCAT;

/***************************************************************************/
THE REST OF THE PROGRAM GENERATES SIMULATED DATA FOR TIME IN
CRIME IN T+1 IF NOT ARRESTED
***************************************************************************/

/***************************************************************************/
THIS STEP CREATES A VAR TOT WHICH IS THE TOTAL (ARREST AND NON-ARREST)
NUMBER OF OBSERVATIONS ON CIT IN EACH SOCIAL CAPITAL BIN, STCAT=1.....5
***************************************************************************/

DATA MAC; SET STEP5A;
PROC SORT; BY STCAT;
PROC MEANS NOPRINT; BY STCAT; VAR CITPLS10;
OUTPUT OUT=OUTMEAN N=TOT;
PROC PRINT DATA=OUTMEAN;

/***************************************************************************/
THIS STEP CREATES MACRO FLAGS FOR THE FIRST AND LAST OBSERVATION ON CIT
IN EACH SOCIAL CAPITAL GROUP SO THE DO LOOP IN THE MACRO
PLOP KNOW WHERE TO BEGIN AND END EACH DO
***************************************************************************/

DATA MAC1; SET OUTMEAN END=EOF;
RETAIN FIRSTOBS 1;
OBS+TOT;
CALL SYMPUT('FIRST'||LEFT(,_N_), FIRSTOBS);
CALL SYMPUT('LAST'||LEFT(,_N_), OBS);
CALL SYMPUT('GROUP'||LEFT(,_N_), TRIM(STCAT));
FIRSTOBS+TOT;
IF EOF THEN CALL SYMPUT('TOTAL',_N_);
RUN;

%MACRO PLOP;
%LOCAL I J;
%DO I=1 %TO &TOTAL;
/*WORK OUT HOW MANY UNOBSTD NONARREST OUTCOME OBS FOR EACH STCAT DIVISION; IE. THE NUMBER OF INDIVIDUALS WHO NEED DATA SIMULATED FOR STATE OF THE WORLD=NONARREST FOR EACH STCAT BIN */
DATA STEP1; SET STEP5A(FIRSTOBS=&&FIRST&I OBS=&&LAST&I);
KEEP STCAT CITPLS10 INTNO YR AARREST JUNK;
JUNK=1; IF AARREST=1 ;
PROC MEANS NOPRINT; BY STCAT; VAR CITPLS10; OUTPUT OUT=ALF N=NUM;
TITLE "GROUP=&&GROUP&I";
PROC SORT DATA=STEP1; BY STCAT;

DATA STEP2; SET ALF;
/*NUM=# MISSING OBS FOR EACH STCAT FROM POP OF THOSE WHO WERE ARRESTED*/
KEEP NUM STCAT JUNK; JUNK=1;
PROC SORT; BY STCAT ;

/* USE ALL REPORTED INFO (FROM ANYONE WHO IS NOT ARRESTED TO CREATE THE CDF FOR CIT, FOR EACH STAT. THE PROB OF EACH CIT IS IN RLT*/
DATA STEP3; SET STEP5A(FIRSTOBS=&&FIRST&I OBS=&&LAST&I);
KEEP STCAT CITPLS10;
IF AARREST=0 ;
PROC SORT; BY CITPLS10;
PROC RANK DATA=STEP3 OUT=ALPHA FRACTION;
RANKS RLT; VAR CITPLS10;

/* OBTAIN UNIQUE OBS FOR CIT AND RLT*/
DATA STEP4; SET ALPHA; BY CITPLS10; IF FIRST.CITPLS10;
KEEP STCAT RLT CITPLS10;
TITLE "GROUP=&&GROUP&I";
PROC PRINT;
PROC SORT; BY STCAT CITPLS10;

DATA STEP6; SET STEP4;
KEEP RLT ;
PROC TRANSPOSE OUT=PART PREFIX=VAR;

DATA STEP6A; SET STEP4;
KEEP CITPLS10 ;
PROC TRANSPOSE OUT=PARTA PREFIX=VAL;

/*THE 'VARS' GIVE THE LOWER AND UPPER BOUNDS WHEN ALLOCATING THE SIMULATED CIT A VALUE,GIVEN BY THE 'VALS'*/
DATA SUN1; SET PART ;
JUNK=1;
/* PROC PRINT; TITLE "GROUP=&&GROUP&I CDF "; */

DATA SUNA; SET PARTA;
JUNK=1;
/* PROC PRINT; TITLE "GROUP=&&GROUP&I LT "; */

DATA SUNDAY; MERGE SUN1 SUNA; BY JUNK;
/* NEED TO ASSOCIATE THE SIMULATED CITs WITH AN INDIVIDUAL SO NEED THE INTNO's AS WELL AS THE STCATs OF THOSE WITH MISSING OBS */
ELSE IF VAR40<X1<=VAR41 THEN SLT=VAL41;
ELSE IF VAR41<X1<=VAR42 THEN SLT=VAL42;
ELSE IF VAR42<X1<=VAR43 THEN SLT=VAL43;
ELSE IF VAR43<X1<=VAR44 THEN SLT=VAL44;
ELSE IF VAR44<X1<=VAR45 THEN SLT=VAL45;
ELSE IF VAR45<X1<=VAR46 THEN SLT=VAL46;
ELSE IF VAR46<X1<=VAR47 THEN SLT=VAL47;
ELSE IF VAR47<X1<=VAR48 THEN SLT=VAL48;
ELSE IF VAR48<X1<=VAR49 THEN SLT=VAL49;
ELSE IF VAR49<X1<=VAR50 THEN SLT=VAL50;
ELSE IF VAR50<X1<=VAR51 THEN SLT=VAL51;
ELSE IF VAR51<X1<=VAR52 THEN SLT=VAL52;
ELSE IF VAR52<X1<=VAR53 THEN SLT=VAL53;
ELSE IF VAR53<X1<=VAR54 THEN SLT=VAL54;
ELSE IF VAR54<X1<=VAR55 THEN SLT=VAL55;
ELSE IF VAR55<X1<=VAR56 THEN SLT=VAL56;
ELSE IF VAR56<X1<=VAR57 THEN SLT=VAL57;
ELSE IF VAR57<X1<=VAR58 THEN SLT=VAL58;
ELSE IF VAR58<X1<=VAR59 THEN SLT=VAL59;
ELSE IF VAR59<X1<=VAR60 THEN SLT=VAL60;
ELSE IF VAR60<X1<=VAR61 THEN SLT=VAL61;
ELSE IF VAR61<X1<=VAR62 THEN SLT=VAL62;
ELSE IF VAR62<X1<=VAR63 THEN SLT=VAL63;
ELSE IF VAR63<X1<=VAR64 THEN SLT=VAL64;
ELSE IF VAR64<X1<=VAR65 THEN SLT=VAL65;
ELSE IF VAR65<X1<=VAR66 THEN SLT=VAL66;
ELSE IF VAR66<X1<=VAR67 THEN SLT=VAL67;
ELSE IF VAR67<X1<=VAR68 THEN SLT=VAL68;
PROC SORT; BY INTNO YR SLT;
/* PROC SORT; BY STCAT;
PROC PRINT; TITLE "GROUP=&GROUP&I": */

%END;
%MEND PLOP;

%PLOP;

DATA SIM; SET PROP1 PROP2 PROP3 PROP4 PROPS;
KEEP INTNO YR SCT10;
SCT10=SLT;
PROC SORT; BY INTNO YR;
/* PROC PRINT; */

DATA STEPS; SET STEP5A;
KEEP INTNO YR N AARREST CITPLS11 CIT;
N=1;
DO UNTIL(N GT 100);
N+1;
OUTPUT;
END;
PROC SORT; BY INTNO YR;

DATA SCTPLS10.DAT; MERGE SIM STEPS; BY INTNO YR;
KEEP INTNO YR SCIT10 AARREST;
IF SCT10=. THEN SCIT10=0; ELSE SCIT10=SCT10;
PROC SORT ; BY INTNO YR;
PROC FREQ; TABLES SCIT10;

CMS FILEDEF OUT DISK SIM2 DATA A;
DATA SIM2.DAT; MERGE STPLS10.DAT STPLS11.DAT SCTPLS10.DAT SCTPLS11.DAT;
BY INTNO YR;
FILE OUT LRECL=34;
PUT @1 INTNO 3. @4 YR 2. @6 SLTPLS10 7.2 @13 SLTPLS11 7.2 @20 SCIT10 7.2
   @27 SCIT11 7.2 @34 AARREST 1.;
APPENDIX 7

FORTRAN PROGRAM FOR THE SIMULATED METHOD OF MOMENTS ESTIMATOR

IMPLICIT REAL*8 (A-H,O-Z)
EXTERNAL FUNC1
EXTERNAL GRADX
C
CHARACTER*8 ALABEL(8)
DATA ALABEL/
  'AI','A2', 'B11','B22','B44',
  'B12','B14','B24'/
C
NEXT ARE DATA ARRAYS
C
DIMENSION B(8), SPD(8,8), FPD(8)
C
DIMENSION DATA(423,5,37)
COMMON/USER1/DATA
COMMON/USER2/NOB,NTIME,NIV,NEQ,NSIM
COMMON/USER3/IFLAG1
COMMON/USER4/S(33,33)
C
FOR NEXT 7 CARDS SEE HANDBOOK
C
COMMON/BFIDIF/FDFRAC,FDMIN
COMMON/BLNSR/STEP1,STPACC,NLNSR
COMMON/BSPD/ISPD
COMMON/BNOBS/NOBS
COMMON/BOPT/IVER,LT,IFP,ISP,NLOOP,IST,ILoop
COMMON/BOPT2/ACC,R,PM1,IVAL,IERL,ITERC,MX,IER
COMMON/BPRINT/IPT,NFILE,NDIG,NPUNCH,IPT,MFILE
COMMON/BREAD/NREAD
COMMON/BINPUT/INFLAG
COMMON/BSTACK/AINT(1000)
COMMON/BSTAK/NQ,NTOP
COMMON/BSTOP/NVAR1,ISTOP(3)
COMMON/BTRAT/ITRFLG
C
SET PARAMETERS FOR OPT
CALL ERRSET(207,300,0,0,0)
CALL ERRSET(208,300,0,0,0)
CALL ERRSET(209,300,0,0,0)
CALL ERRSET(262,300,0,0,0)
CALL ERRSET(261,300,0,0,0)
CALL ERRSET(263,300,0,0,0)
CALL ERRSET(245,300,0,0,0)
C
SET UP THE PARAMETERS FOR GQOPT
C
ITERL= 50
C ITERL=10
C ITERL=0
C ITRFLG=0
C MAX=1
C ACC=1.0D-5
C NP=8
C NSIZE=NP*NP
C IER=-2
C
C OPTIONS FOR GRADX
C IVER=2
C IFP=3
C FDFRAC=0.0001D0
C FDMIN=0.00000001D0
C
C NQ=1000
C NEQ=3
C NIV=11
C NTIME=5
C NOB=423
C NSIM=100
C IORTHOG=NEQ*NIV
C
C NREAD=12
C NPUNCH=11
C
C SET TO 0 IF NO READ FROM UNIT 12 AND 1 OTHERWISE
C
C INFO=1
C
C NVAR=37
C SNVAR=7
C
C READ IN THE DATA
C DO 1001 I=1, NOB
C DO 1001 J=1, NTIME
C READ(13,9934) (DATA(I,J,K),K=1,NVAR)
C
9934 FORMAT(F3.0,F2.0,
C 1 9F7.2, 3F8.2, 2F7.2, 9F4.2, 9F1.0, 2F2.0, 4F4.2, F6.4)
C PRINT 9933,I,J,(DATA(I,J,K),K=33,37)
C
9933 FORMAT(5X,2I5,8E13.5)
C 1001 CONTINUE
C
C PRINT 9933,I,J,(DATA(I,J,K),K=9,16)
C C PRINT 9933,I,J,(DATA(I,J,K),K=17,24)
C C PRINT 9933,I,J,(DATA(I,J,K),K=25,32)
C C PRINT 9933,I,J,(DATA(I,J,K),K=33,37)
C
C******************************************************************************
C
C GRADX ALGORITHM
C
C 28 FORMAT(5X,E13.5)
C C SET UP CALLING PARAMETERS
C C DO 1990 I=1,NP
C C READ(20,1002) K,B(I)
1990 CONTINUE
C SET IFLAG1 = 0 IF CALCULATING A NEW WEIGHTING MATRIX-
C
C IFLAG1=1
C WRITE OUT A NEW WEIGHTING MATRIX BASED ON THE GMM ESTIMATES***
CALL FUNC1(B,NP,F)
PRINT 28,F
DO 7654 I=1,1ORTHOG
READ(22,7653) K, (S(I,J),J=1,I)
WRITE(22,7653) I,(S(I,J),J=1,I)
7653 FORMAT(2X,I4,8E13.5/,6X,8E13.5/,6X,8E13.5/,6X,8E13.5/,6X,
1 8E13.5)
7654 CONTINUE
DO 19 I=1,1ORTHOG
DO 19 J=1,I,1ORTHOG
19 S(I,J)=S(J,I)
C
C CALL FUNC1(B,NP,F)
C PRINT 28,F
C
C IF(NOB.GT.0) GOTO 9923
NQ=1000
DO 1006 I=1,NP
READ(20,1002) J, B(I)
1006 CONTINUE
C IF(NOB.GT.0) GOTO 9923
CALL OPT(B,NP,F,GRADX,ITERL,MAX,IER,ACC,FUNC1,ALABEL)
DO 1005 I=1,NP
WRITE(21,1002) I,B(I)
1005 CONTINUE
CALL OPTOUT(3)
C IF(NOB.GT.0) GOTO 9923
CALL PUNCH(B,NP)
CALL OPTMOV(1,SPD,NSIZE)
STOP
END

*****************************************************************************
C THE FOLLOWING SUBROUTINE CALCULATES THE FUNCTION TO BE OPTIMIZED
*****************************************************************************

SUBROUTINE FUNC1(BB,NP,SSE,*)
IMPLICIT REAL*8 (A-H,O-Z)

C DIMENSION BB(NP),FPD(8)
C
C REAL*8 DATA,F1,F2,F3,F4,F5
REAL*8 N1,N2,N3,N4,N5,N6,N7,N8,LT,LTPLU10,MOVE
1 LTPLU11, MARRY, NMUM, NUMKIDS, NPC,INTNO
DIMENSION DATA(423,5,37)
DIMENSION F1(423,6,11),F2(423,6,11),F3(423,6,11),F4(423,6,11),
IF5(423,6,11),ORTHOG(33),F11(11),F22(11),F33(11),S(33,33),
2 F44(11), F55(11)

C C COMMUNICATE DATA TO THE FUNCTION
C SUBROUTINE
C
COMMON USER1/ DATA
COMMON USER2/ NOB, NTIME, NIV, NEQ, NSIM
COMMON USER3/ IFLAG1
COMMON USER4/ S

XNOB=NOB
XNSIM=NSIM
XIT=NTIME
NIVTWO=2*NIV
NIVTHRE=3*NIV
NIVFOR=4*NIV
IORTHG=NIV*NEQ
C SET UP PARAMETERS
A4=1
A1=BB(1)**2
A2=BB(2)**2
B11=BB(3)
B22=BB(4)
B44=BB(5)
B12=BB(6)
B14=BB(7)
B24=BB(8)
N1=.0702
N2=.0000020
N3=.000100
N4=19.58
N5=.0110
N6=.16
N7=.0183
N8=.000054
C2=.185
C1=.5936
AMAXH=5824.0D0
C
DO 222 I = 1, NOB
DO 222 J = 1, NTIME
COUNT=0.0
SUMYL=0.0
SUMYC=0.0
SUMY=0.0
5 IF (COUNT.LT.NSIM) THEN
   COUNT=COUNT+1
   READ(19,9962) X1, X2, SLT10, SLT11, SCIT10, SCIT11, AARREST
9962 FORMAT(F3.0, F2.0, 4F7.2, F1.0)
C LOAD IN JENNY'S MODEL
INTNO=DATA(I,J,1)
YR=DATA(I,J,2)
LT=DATA(I,J,3)
CIT=DATA(I,J,4)
XT=DATA(I,J,5)
LTPLU10=DATA(I,J,6)
CITPL10=DATA(I,J,7)
XTPL10=DATA(I,J,8)
LTPLU11=DATA(I,J,9)
CITPL11=DATA(I,J,10)
XTPL11=DATA(I,J,11)
SC=DATA(I,J,12)
SCTPL10=DATA(I,J,13)
SCTPL11=DATA(I,J,14)
RLABINC=DATA(I,J,15)
RCINC=DATA(I,J,16)
Y=DATA(I,J,17)
YL=DATA(I,J,18)
YC=DATA(I,J,19)
WL=DATA(I,J,20)
WC=DATA(I,J,21)
ED2=DATA(I,J,22)
ED3=DATA(I,J,23)
SCH=DATA(I,J,24)
MARRY=DATA(I,J,25)
NMUM=DATA(I,J,26)
WHITE=DATA(I,J,27)
SES=DATA(I,J,28)
DEFACTO=DATA(I,J,29)
MOVE=DATA(I,J,30)
NUMKIDS=DATA(I,J,31)
NPC=DATA(I,J,32)
D=DATA(I,J,33)
B=DATA(I,J,34)
G=DATA(I,J,35)
P=DATA(I,J,36)
A=DATA(I,J,37)

C RESCALE SOCIAL CAPITAL
SC=SC/100.
SCTPL11=SCTPL11/100.
SCTPL10=SCTPL10/100.
FT=5824.0D0-LT-CIT
FTPL10=5824.0D0-LTPLU10-CITPL10
FTPL11=5824.0D0-LTPLU11-CITPL11
G=G/100.

C*******************************************************************************

YL=0.0
YC=0.0
Y=0.0

C ED=0.0
IF (ED2.EQ.1 .OR. ED3.EQ.1) THEN
  ED=1.
END IF

C IF (AARREST.EQ.0) THEN
LTPLU11=SLT11
CITPL11=SCIT11
FTPL11=AMAXH-LTPLU11-CITPL11
WLTL11=C1+(N1+N2*LTPLU11+N3*SCTPL11+N5*ED)*LTPLU11+N4*ED+N6*SCH
WCT11=C2+(N7+N8*CITPL11)*CITPL11
XTPL11=WLTL11+WCT11
ELSE IF (AARREST.EQ.1) THEN
  LTPLU10=SLT10
  CITPL10=SCIT10
  FTPL10=AMAXH-LTPLU10-CITPL10
  WLT10=C1+(N1+N2*LTPLU10+N3*CITPL10+N5*ED)*LTPLU10+N4*ED+N6*SCH
  WCT10=C2+(N7+N8*CITPL10)*CITPL10
  XTPL10=WLT10+WCT10
END IF
C
IF (AARREST.EQ.0 .AND. XTPL11.LT.0.0) THEN
  XTPL11=10
END IF
C
IF (AARREST.EQ.1 .AND. XTPL10.LT.0.0) THEN
  XTPL10=10
END IF
C
IF (AARREST.EQ.1 .AND. FTPL10.LT.0.0) THEN
  FTPL10=214
END IF
C
C DERIVATIVES OF THEUTILITY AND INCOME FUNCTIONS
C
UIT=(A1+B1*DLOG(XT)+B12*DLOG(FT)+B14*DLOG(SC))/XT
UIT10=(A1+B11*DLOG(XTPL10)+B12*DLOG(FTPL10)+B14*DLOG(SCTPL10))
  /XTPL10
UIT11=(A1+B11*DLOG(XTPL11)+B12*DLOG(FTPL11)+B14*DLOG(SCTPL11))
  /XTPL11
U2T=(A2+B2*DLOG(FT)+B12*DLOG(XT)+B24*DLOG(SC))/FT
U2T10=(A2+B22*DLOG(FTPL10)+B12*DLOG(XTPL10)+B24*DLOG(SCTPL10))
  /FTPL10
U2T11=(A2+B22*DLOG(FTPL11)+B12*DLOG(XTPL11)+B24*DLOG(SCTPL11))
  /FTPL11
U4T=(A4+B4*DLOG(SC)+B14*DLOG(XT)+B24*DLOG(FT))/SC
U4T10=(A4+B44*DLOG(SCTPL10)+B14*DLOG(XTPL10)+B24*DLOG(FTPL10))
  /SCTPL10
U4T11=(A4+B44*DLOG(SCTPL11)+B14*DLOG(XTPL11)+B24*DLOG(FTPL11))
  /SCTPL11
WLT=N1+2*N2*LT+N3*SC+N5*ED
WL1T10=N1+2*N2*LTPLU10+N3*CITPL10+N5*ED
WL1T11=N1+2*N2*LTPLU11+N3*CITPL11+N5*ED
WL2T=N3*LT
WL2T10=N3*LTPLU10
WL2T11=N3*LTPLU11
WCIT=N7+2*N8*CIT
WC1T10=N7+2*N8*CITPL10
WC1T11=N7+2*N8*CITPL11
A10=(WL2T10+((1.0D0-D*A*CITPL10)/(A*CITPL10))*WC1T10
  -(1.0D0-D)*WL1T10/G)
A11=(WL2T11+((1.0D0-D*A*CITPL11)/(A*CITPL11))*WC1T11
  -(1.0D0-D)*WL1T11/G)
A20=((1.0D0-D/G)-((1.0D0-D-A*CITPL10)/(A*CITPL10))
A21=((1.0D0-D/G)-((1.0D0-D-A*CITPL11)/(A*CITPL11))
C
YL = UI1*T*WL1*T-U2*T+B*G*(1.0D0-P)*(U4*T10+A10*UI1*T+A20*U2*T10)
Y = UI1*T-B*1.03D0*(P*UI1*T+(1.0D0-P)*U1*T10)

C
C START CALCULATIONS HERE
SUMYL = SUMYL + YL
SUMYC = SUMYC + YC
SUMY = SUMY + Y
GOTO 45
ELSE IF (COUNT.GE.NSIM) THEN
   S1 = SUMYL/XNSIM
   S2 = SUMYC/XNSIM
   S3 = SUMY/XNSIM
ENDIF

C
DO 2 K = 1, NIV
   Z = DATA(I,J,K+21)
   F1(I,J,K) = S1*Z
   F2(I,J,K) = S2*Z
   F3(I,J,K) = S3*Z
C PRINT 9998, I,J,K,INTNO,YR,YL,F1(I,J,K)
   2 CONTINUE
222 CONTINUE
REWIND 19
9998 FORMAT(2X,3I4,2X,5E13.5,/,12X,5E13.5)

C
DO 5 K = 1, NIV
DO 5 I = 1, NOB
   ASUM = 0.0
   BSUM = 0.0
   CSUM = 0.0
   DO 4 J = 1, NTIME
      ASUM = ASUM + F1(I,J,K)
      BSUM = BSUM + F2(I,J,K)
      CSUM = CSUM + F3(I,J,K)
   4 CONTINUE
F1(I,6,K) = ASUM/XIT
F2(I,6,K) = BSUM/XIT
F3(I,6,K) = CSUM/XIT
5 CONTINUE
IF(IFLAG1.EQ.1) GOTO 15

C
C CALCULATE THE WEIGHTING MATRIX

C THIS JUST SETS THE MATRIX TO AN IDENTITY
DO 21 I = 1, IORTHG
DO 21 J = 1, IORTHG
   S(I,J) = 0.0D0
   IF(I.EQ.J) S(I,J) = 1.0D0
21 CONTINUE

C LOOP OVER THE COVARIANCE MATRIX CALCULATION
C ******************************************************
IF(NOB.GT.0) GOTO 15
C ****************************************************
DO 17 I=1,JORTHG
DO 17 J=1,JORTHG
ASUM=0.0D0
DO 18 JJ=1,NOB
IF((L.LE.NIV).AND.(J.LE.NIV)) ASUM=ASUM+F1(JJ,6,I)*F1(JJ,6,J)
IF((L.LE.NIV).AND.(J.GT.NIV).AND.(J.LE.NIVTWO)) ASUM=ASUM+
1 F1(JJ,6,I)*F2(JJ,6,J-NIV)
IF((L.LE.NIV).AND.(J.GT.NIVTWO)) ASUM=ASUM+F1(JJ,6,I)*
1 F3(JJ,6,J-NIVTWO)
1 ASUM=ASUM+F1(JJ,6,I-NIV)*F2(JJ,6,J-NIV)
IF((L.GT.NIV).AND.(J.LE.NIVTWO).AND.(J.GT.NIVTWO)) ASUM=ASUM+
1 F2(JJ,6,I-NIV)*F3(JJ,6,J-NIVTWO)
IF((L.GT.NIVTWO).AND.(J.GT.NIVTWO)) ASUM=ASUM+F3(JJ,6,I-NIVTWO)*
1 F3(JJ,6,J-NIVTWO)
18 CONTINUE
17 S(I,J)=ASUM
DO 19 I=1,JORTHG
DO 19 J=1,1
19 S(I,J)=S(I,J)
C
CALL INVERT(S,IORTHG,IORTHG)
C
15 CONTINUE
C END OF WEIGHTING MATRIX CALCULATION
DO 7 K=1,NIV
ASUM=0.0
BSUM=0.0
CSUM=0.0
DO 6 I=1,NOB
ASUM=ASUM+F1(I,6,K)
BSUM=BSUM+F2(I,6,K)
CSUM=CSUM+F3(I,6,K)
6 CONTINUE
F11(K)=ASUM/XNOB
F22(K)=BSUM/XNOB
F33(K)=CSUM/XNOB
7 CONTINUE
C
DO 8 K=1,JORTHG
IF(K.LE.NIV) ORTHOG(K)=F11(K)
IF((K.GT.NIV).AND.(K.LE.NIVTWO)) ORTHOG(K)=F22(K-NIV)
IF((K.GT.NIVTWO).AND.(K.LE.NIVTHRE)) ORTHOG(K)=F33(K-NIVTWO)
8 CONTINUE
C DO 7777 I=1,JORTHG
C PRINT 7778, 1, ORTHOG(I)
7777 CONTINUE
7778 FORMAT(5X,I4,E13.5)
C
SSE=0.0
DO 10 I=1,JORTHG
DO 10 J=1,JORTHG
SSE=SSE+ORTHOG(I)*S(I,J)*ORTHOG(J)
10 SSE=-SSE
11 CONTINUE
RETURN
END
APPENDIX 8

FORTRAN PROGRAM FOR ASYMPTOTIC STANDARD ERRORS FOR THE
SIMULATED METHOD OF MOMENTS ESTIMATOR

IMPLICIT REAL*8 (A-H,O-Z)
EXTERNAL FUNC1
EXTERNAL GRADX

C
CHARACTER*8 ALABEL(8)
DATA ALABEL/
1 'A1','A2', 'B11','B22','B44',
1 'B12','B14','B24'/

C
NEXT ARE DATA ARRAYS

C
DIMENSION B(8), SPD(8,8)

C
DIMENSION DATA(423,5,37)
COMMON USER1/DATA
COMMON USER2/NOB,NTIME,NIV,NEQ,NSIM
COMMON USER3/IFLAG1
COMMON USER4/S(33,33)

C
FOR NEXT 7 CARDS SEE HANDBOOK

C
COMMON BFIDIF/FDFRAC,FDMIN
COMMON BLNSR/STEP1,STPACC,NLNSR
COMMON BSPD/ISPD
COMMON BNOBS/NOBS
COMMON BOPT/IVER,LT,IFP,ISP,NLOOP,IST,ILOOP
COMMON BOPT2/ACC,R,PM1,IVAL,IERL,ITERC,MX,IER
COMMON BPRINT/IPT,NFILE,NDIG,NPUNCH,JPT,MFILE
COMMON BREAD/NREAD
COMMON BINPUT/INFLAG
COMMON BSTACK/AIN1(1000)
COMMON BSTACK/NQ,NTOP
COMMON BSTOP/NVAR1,ISTOP(3)
COMMON BTRAT/ITRFLG

C
SET PARAMETERS FOR OPT
CALL ERRSET(207,300 ,0,0,0)
CALL ERRSET(208,300,0,0,0)
CALL ERRSET(209,300,0,0,0)
CALL ERRSET(262,300,0,0,0)
CALL ERRSET(261,300,0,0,0)
CALL ERRSET(263,300,0,0,0)
CALL ERRSET(245,300,0,0,0)

C
C SET UP THE PARAMETERS FOR GQOPT
C IVERL= 50
    IVERL=10
C ITRFLG=0
    ITRFLG=0
    MAX=1
    ACC=1.0D-3
    NP=8
    NSIZE=NP*NP
    IER=-2
C
C OPTIONS FOR GRADX
    IVER=2
    IFP=3
    FDFRAC=0.0001D0
    FDMIN=0.00000001D0
    STEP1=1.
    ISP=1
    IST=1
    NQ=4*NP*NP+6*NP
    NQ=1000
    NEQ=3
    NIV=11
    NTIME=5
    NOB=423
    NSIM=1
    IORTHOG=NEQ*NIV
C
    NREAD=12
    NPUNCH=11
C
C SET TO 0 IF NO READ FROM UNIT 12 AND 1 OTHERWISE
C
    INFLAG=0
C
    NVAR=37
    SNVAR=7
C
C READ IN THE DATA
DO 1001 I=1, NOB
DO 1001 J=1, NTIME
    READ(13,9934) (DATA(I,J,K),K=1,NVAR)
9934 FORMAT(F3.0,F2.0,
1 9F7.2, 3F8.2, 2F7.2, 5F4.2,9F1.0,2F2.0, 4F4.2, F6.4)
C PRINT 9933,1,I,(DATA(I,J,K),K=33,37)
9933 FORMAT(5X,2I5,8E13.5)
1001 CONTINUE
C
C GRADX ALGORITHM
C
    28 FORMAT(5X,E13.5)
C SET UP CALLING PARAMETERS
DO 1990 I=1,NP
READ(20,1002) K,B(I)
1990 CONTINUE
C
C SET IFLAG1 = 0 IF CALCULATING A NEW WEIGHTING MATRIX
C
IFLAG1 = 1
C
C WRITE OUT A NEW WEIGHTING MATRIX BASED ON THE GMM ESTIMATES
C CALL FUNC1(B,NP,F)
C PRINT 28,F
DO 7654 I = 1, lORTHO
    READ(22,7653) K, (S(I,J), J = 1, I)
C WRITE(22,7653) I, (S(I,J),J = 1, I)
C
7653 FORMAT(2X,I4,8E13.5/,6X,8E13.5/,6X,8E13.5/,6X,8E13.5/,6X,8E13.5/,6X,
      1 8E13.5)
7654 CONTINUE
DO 19 I = 1, lORTHO
DO 19 J = 1, lORTHO
19 S(I,J) = S(I,J)
C
CALL FUNC1(B,NP,F)
PRINT 28,F
C
IF(NOB.GT.0) GOTO 9923
NO = 1000
DO 1006 I = 1, NP
C READ(20,1002) J, B(I)
1006 CONTINUE
DO 1055 I = 1, NP
C WRITE(27,1002) I,FPD(I)
1055 CONTINUE
C IF(NOB.GT.0) GOTO 9923
CALL OPT(B,NP,F,GRADX,ITERL,MATLJER,ACC,FUNC1,ALABEL)
DO 1005 I = 1, NP
WRITE(21,1002) I,B(I)
1005 CONTINUE
CALL OPTOUT(3)
IF(NOB.GT.0) GOTO 9923
C CALL PUNCH(B,NP)
C CALL OPTMOV(1,SPD,NSIZE)
STOP
END
C
C***********************************************************************
C THE FOLLOWING SUBROUTINE CALCULATES THE STANDARD ERRORS
C***********************************************************************
C SUBROUTINE FUNC1(BB,NP,SSE,*)
IMPLICIT REAL*8 (A-H,O-Z)
C
REAL*8 DATA,F1,F2,F3,F1STAR,F2STAR,F3STAR,OS,DSD,DER
REAL*8 N1,N2,N3,N4,N5,N6,N7,N8,LT,LTPLU10,MOVLT18,MUMWK,MOVE
1 LTPLU11, MARRY, NMUM, NUMKIDS, NPC,INTNO
DIMENSION BB(NP)
DIMENSION DATA(423,5,37)
DIMENSION F1(423,6,11),F2(423,6,11),F3(423,6,11),
1 F1STAR(423,6,11,8),F2STAR(423,6,11,8),F3STAR(423,6,11,8),
1 ORTHOG(33),F11(11),F22(11),F33(11),S(33,33), OS(33), DSD(8,8),
2 F11STAR(11,8), F22STAR(11,8), F33STAR(11,8), DER(33,8), DS(8,33)

C
COMMUNICATE DATA TO THE FUNCTION

COMMON/USER1/DATA
COMMON/USER2/NOB,NTIME,NIV,NEQ,NSIM
COMMON/USER3/IFLAG1
COMMON/USER4/S
IER=-2
XNSIM=NSIM
XNOB=NOB
XTT=NTIME
NIVTWO=2*NIV
NIVTHRE=3*NIV
NIVFOR=4*NIV
IORTHG=NIV*NEQ

C
SET UP PARAMETERS
A4=1
A1=BB(1)**2
A2=BB(2)**2
B11=BB(3)
B22=BB(4)
B44=BB(5)
B12=BB(6)
B14=BB(7)
B24=BB(8)
N1=.0702
N2=.000002
N3=.0001
N4=-19.58
N5=.011
N6=-1.16
N7=.018
N8=.000054
C1=.5936
C2=0.185
AMAXH=5824.0D0

C
DO 222 I = 1,NOB
DO 222 J = 1,NTIME

C
COUNT=0.0
SME1A2=0.0
SME1A4=0.0
SME1B11=0.0
SME1B22=0.0
SME1B44=0.0
SME1B12=0.0
SME1B14=0.0
SME1B24=0.0
SMEE2A1=0.0
SMEE2A4=0.0
SMEE2B11=0.0
SMEE2B22=0.0
SMEE2B44=0.0
SMEE2B12=0.0
SMEE2B14=0.0
SMEE2B24=0.0
SMEE3A2=0.0
SMEE3A4=0.0
SMEE3B11=0.0
SMEE3B22=0.0
SMEE3B44=0.0
SMEE3B12=0.0
SMEE3B14=0.0
SMEE3B24=0.0

45 IF (COUNTLT.NSIM) THEN
   COUNT=COUNT+1
   READ(19,9962) X1,X2,SLT10,SLT11,SCIT10,SCIT11,AARREST
   9962 FORMAT(F3.0,F2.0,4F7.2,F1.0)

C LOAD IN JENNY'S MODEL
INTNO=DATA(I,J,1)
YR=DATA(I,J,2)
LT=DATA(I,J,3)
CIT=DATA(I,J,4)
XT=DATA(I,J,5)
LTPLU10=DATA(I,J,6)
CITPL10=DATA(I,J,7)
XTPL10=DATA(I,J,8)
LTPLU11=DATA(I,J,9)
CITPL11=DATA(I,J,10)
XTPL11=DATA(I,J,11)
SC=DATA(I,J,12)
SCITPL10=DATA(I,J,13)
SCITPL11=DATA(I,J,14)
RLABINC=DATA(I,J,15)
RCINC=DATA(I,J,16)
Y=DATA(I,J,17)
YL=DATA(I,J,18)
YC=DATA(I,J,19)
WL=DATA(I,J,20)
WC=DATA(I,J,21)
ED2=DATA(I,J,22)
ED3=DATA(I,J,23)
SCH=DATA(I,J,24)
MARRY=DATA(I,J,25)
NMUM=DATA(I,J,26)
MOV1LT18=DATA(I,J,27)
MUMWK=DATA(I,J,28)
DEFACTO=DATA(I,J,29)
MOVE=DATA(I,J,30)
NUMKIDS=DATA(I,J,31)
NPC=DATA(I,J,32)
D=DATA(I,J,33)
B=DATA(I,J,34)
G=DATA(I,J,35)
P=DATA(I,J,36)
A=DATA(I,J,37)

C     RESCALE SOCIAL CAPITAL
SC=SC/100.
SCTPL11=SCTPL11/100.
SCTPL10=SCTPL10/100.
FT=5824.0D0-LT-CIT
FTPL10=5824.0D0-LTPLU10-CITPL10
FTPL11=5824.0D0-LTPLU11-CITPL11
G=G/100.

C     END OF DATA STEP
C

YL=0.0
YC=0.0
Y=0.0
EE1A1=0.0
EE1A2=0.0

C     EE1A4=0.0
EE1B11=0.0
EE1B22=0.0
EE1B44=0.0
EE1B12=0.0
EE1B14=0.0
EE1B24=0.0
EE2A1=0.0
EE2A2=0.0

C     EE2A4=0.0
EE2B11=0.0
EE2B22=0.0
EE2B44=0.0
EE2B12=0.0
EE2B14=0.0
EE2B24=0.0
EE3A1=0.0
EE3A2=0.0

C     EE3A4=0.0
EE3B11=0.0
EE3B22=0.0
EE3B44=0.0
EE3B12=0.0
EE3B14=0.0
EE3B24=0.0

C     ED=0.0
     IF (ED2 .EQ. 1 .OR. ED3 .EQ. 1) THEN
     ED=1.
     END IF

C     IF (AARREST.EQ.0) THEN
     LTPLU11=SLT11
     CITPL11=SCIT11
     FTPL11=AMAXH-LTPLU11-CITPL11
\[ \text{WLT11} = (C1 + (N1 + N2 \times \text{LTPLU11} + N3 \times \text{SCTPL11} + N5 \times \text{ED}) \times \text{LTPLU11} + N4 \times \text{ED} + N6 \times N5 + N7 + N8 \times \text{CITPL11} + N9 \times \text{CITPL11}) \]

\[ \text{WCT11} = (C2 + (N7 + N8 \times \text{CITPL11}) + N10 \times \text{CITPL11}) \]

\[ \text{XTPL10} = \text{WLT11} + \text{WCT11} \]

ELSE IF (\( \text{AARREST \_ EQ \_ 0} \) \( \text{AND} \) \( \text{XTPL11} < 0 \)) THEN

\[ \text{XTPL10} = \text{SLT10} \]

\[ \text{CITPL10} = \text{SCIT10} \]

\[ \text{FTPPL10} = \text{AMAXX} \times \text{LTPLU10} + \text{CITPL10} \]

\[ \text{WLT10} = (C1 + (N1 + N2 \times \text{LTPLU10} + N3 \times \text{SCTPL10} + N5 \times \text{ED}) \times \text{LTPLU10} + N4 \times \text{ED} + N6 \times N5 + N7 + N8 \times \text{CITPL10}) \]

\[ \text{WCT10} = (C2 + (N7 + N8 \times \text{CITPL10}) + N10 \times \text{CITPL10}) \]

\[ \text{XTPL10} = \text{WLT10} + \text{WCT10} \]

\] END IF

C

IF (\( \text{AARREST \_ EQ \_ 0} \) \( \text{AND} \) \( \text{XTPL11} \leq 0 \)) THEN

\[ \text{XTPL11} = 10 \]

\] END IF

C

IF (\( \text{AARREST \_ EQ \_ 1} \) \( \text{AND} \) \( \text{XTPL10} < 0 \)) THEN

\[ \text{XTPL10} = 10 \]

\] END IF

C

IF (\( \text{AARREST \_ EQ \_ 1} \) \( \text{AND} \) \( \text{FTPPL10} < 0 \)) THEN

\[ \text{FTPPL10} = 214 \]

\] END IF

C

C

DERIVATIVES OF THE UTILITY AND INCOME FUNCTIONS

\[ \text{UIT1} = (A1 + B11 \times \text{DLOG} \_ \text{XT}) + B12 \times \text{DLOG} \_ \text{FT} + B14 \times \text{DLOG} \_ \text{SC}) \div \text{XT} \]

\[ \text{UIT10} = (A1 + B11 \times \text{DLOG} \_ \text{XTPL10}) + B12 \times \text{DLOG} \_ \text{FTPPL10} + B14 \times \text{DLOG} \_ \text{SCTPL10}) \]

\[ 1 \div \text{XTPL10} \]

\[ \text{UIT11} = (A1 + B11 \times \text{DLOG} \_ \text{XTPL11}) + B12 \times \text{DLOG} \_ \text{FTPPL11} + B14 \times \text{DLOG} \_ \text{SCTPL11}) \]

\[ 1 \div \text{XTPL11} \]

\[ \text{UIT2} = (A2 + B22 \times \text{DLOG} \_ \text{FT}) + B12 \times \text{DLOG} \_ \text{XT} + B24 \times \text{DLOG} \_ \text{SC}) \div \text{FT} \]

\[ \text{UIT20} = (A2 + B22 \times \text{DLOG} \_ \text{FTPPL10}) + B12 \times \text{DLOG} \_ \text{XTPL10} + B24 \times \text{DLOG} \_ \text{SCTPL10}) \]

\[ 1 \div \text{FTPPL10} \]

\[ \text{UIT21} = (A2 + B22 \times \text{DLOG} \_ \text{FTPPL11}) + B12 \times \text{DLOG} \_ \text{XTPL11} + B24 \times \text{DLOG} \_ \text{SCTPL11}) \]

\[ 1 \div \text{FTPPL11} \]

\[ \text{UIT4} = (A4 + B44 \times \text{DLOG} \_ \text{SC}) + B14 \times \text{DLOG} \_ \text{XT} + B24 \times \text{DLOG} \_ \text{FT}) \div \text{SC} \]

\[ \text{UIT40} = (A4 + B44 \times \text{DLOG} \_ \text{SCTPL10}) + B14 \times \text{DLOG} \_ \text{XTPL10} + B24 \times \text{DLOG} \_ \text{FTPPL10}) \]

\[ 1 \div \text{SCTPL10} \]

\[ \text{UIT41} = (A4 + B44 \times \text{DLOG} \_ \text{SCTPL11}) + B14 \times \text{DLOG} \_ \text{XTPL11} + B24 \times \text{DLOG} \_ \text{FTPPL11}) \]

\[ 1 \div \text{SCTPL11} \]

\[ \text{WLT1} = N1 + 2 \times N2 \times \text{LT} + N3 \times \text{SC} + N5 \times \text{ED} \]

\[ \text{WLT10} = N1 + 2 \times N2 \times \text{LTPLU10} + N3 \times \text{SCTPL10} + N5 \times \text{ED} \]

\[ \text{WLT11} = N1 + 2 \times N2 \times \text{LTPLU11} + N3 \times \text{SCTPL11} + N5 \times \text{ED} \]

\[ \text{WL2T} = N3 \times \text{LT} \]

\[ \text{WL2T10} = N3 \times \text{LTPLU10} \]

\[ \text{WL2T11} = N3 \times \text{LTPLU11} \]

\[ \text{WCT1} = N7 + 2 \times N8 \times \text{CIT} \]

\[ \text{WCT10} = N7 + 2 \times N8 \times \text{CITPL10} \]

\[ \text{WCT11} = N7 + 2 \times N8 \times \text{CITPL11} \]

C

\[ A10 = (\text{WL2T10} + ((1.0D0 - D \times \text{CITPL10}) \times (A \times \text{SCTPL10}) \times \text{WCT10}) \]

\[ - (1.0D0 - D) \times \text{WL2T11} \times \text{G}) \]

\[ A11 = (\text{WL2T11} + ((1.0D0 - D \times \text{CITPL11}) \times (A \times \text{SCTPL11}) \times \text{WCT11}) \]

\[ C \]
CALCULATIONS START HERE

C

EE1A1 = (WL1T/XT) + (B*G*(1.0D0-P)*A10)/XTPL10
EE2A1 = (WC1T/XT) - B*A*P*(SC/XTPL11)/XTPL11
EE3A1 = (1.0D0/XT) - B*(1.030D0)*((P/XTPL11) + (1.0D0-P)/XTPL10)
EE1A2 = -(1.0D0/FT) + B*G*((1.0D0-P)/FTPL10)*A20
EE2A2 = -(1.0D0/FT) - B*A*P*(SC/FTPL11)/A21
EE3A2 = 0.0D0

C

EE1A4 = B*G*((1.0D0-P)/SCTPL10)
EE2A4 = B*A*P*(SC/SCTPL11)

C

EE3A4 = 0.0D0

EE1B1 = (WL1T*DLOG(FT)/XT) - B*G*((1.0D0-P)*DLOG(FTPL10)/XTPL10)*A10
EE2B1 = (WC1T*DLOG(FT)/XT) - B*A*P*(SC*DLOG(FTPL11)/XTPL11)*A11
EE3B1 = (DLOG(FT)/XT) + B*(1.030D0)*((P*DLOG(FTPL11)/XTPL11)
1 + (1.0D0-P)*DLOG(FTPL10)/XTPL10)
EE1B2 = -(DLOG(FT)/FT) + B*G*((1.0D0-P)*DLOG(FTPL10)/FTPL10)*A20
EE2B2 = -(DLOG(FT)/FT) - B*A*P*(SC*DLOG(FTPL11)/FTPL11)*A21
EE3B2 = 0.0D0

EE1B4 = B*G*((1.0D0-P)*DLOG(SCTPL10)/SCTPL10)
EE2B4 = B*A*P*(SC*DLOG(SCTPL11)/SCTPL11)

EE3B4 = 0.0D0

EE1B12 = (WL1T*DLOG(SC)/XT) - (DLOG(FT)/FT) + B*G*(1.0D0-P)*
1 *((DLOG(FTPL10)/XTPL10)*A10 + (DLOG(FTPL10)/FTPL10)*A20)
EE2B12 = (WC1T*DLOG(SC)/XT) - (DLOG(FT)/FT) - B*A*P*SC*
1 *((DLOG(FTPL11)/XTPL11)*A11 + (DLOG(FTPL11)/FTPL11)*A21)
EE3B12 = (DLOG(SC)/XT) - B*(1.030D0)*((P*DLOG(FTPL11)/XTPL11)
1 + (1.0D0-P)*DLOG(FTPL10)/XTPL10)
EE1B14 = (WL1T*DLOG(SC)/XT) + B*G*((1.0D0-P)*((DLOG(SCTPL10)/XTPL10)
1 *A10 + DLOG(FTPL10)/SCTPL10)
EE2B14 = (WC1T*DLOG(SC)/XT) - B*A*P*SC*((DLOG(SCTPL11)/XTPL11)*A11
1 + DLOG(FTPL11)/SCTPL11)
EE3B14 = (DLOG(SC)/XT) + B*(1.030D0)*((P*DLOG(SCTPL11)/XTPL11)
1 + (1.0D0-P)*DLOG(SCTPL10)/XTPL10)
EE1B24 = -(DLOG(SC)/FT) + B*G*((1.0D0-P)*((DLOG(SC)/FTPL10)*A20
1 + DLOG(FTPL10)/SCTPL10)
EE2B24 = -(DLOG(SC)/FT) - B*A*P*SC*((DLOG(SCTPL11)/FTPL11)*A21
1 + DLOG(FTPL11)/SCTPL11)
EE3B24 = 0.0D0

C

PRINT 9998, L, K, DATA (I, J, 32)

4321 CONTINUE

SME1A2 = SME1A2 + EE1A2
SME1A4 = SME1A4 + EE1A4
SME1B11 = SME1B11 + EE1B11
SME1B22 = SME1B22 + EE1B22
SME1B44 = SME1B44 + EE1B44
SME1B12 = SME1B12 + EE1B12
SME1B14 = SME1B14 + EE1B14
SME1B24 = SME1B24 + EE1B24
SME2A2 = SME2A2 + EE2A2
SME2A4=SME2A4+EE2A4
SME2B11=SME2B11+EE2B11
SME2B22=SME2B22+EE2B22
SME2B44=SME2B44+EE2B44
SME2B12=SME2B12+EE2B12
SME2B14=SME2B14+EE2B14
SME2B24=SME2B24+EE2B24
SME3A2=SME3A2+EE3A2
SME3A4=SME3A4+EE3A4
SME3B11=SME3B11+EE3B11
SME3B22=SME3B22+EE3B22
SME3B44=SME3B44+EE3B44
SME3B12=SME3B12+EE3B12
SME3B14=SME3B14+EE3B14
SME3B24=SME3B24+EE3B24
GOTO 45
ELSE IF (COUNT.GE.NSIM) THEN
    AE1A2=SME1A2/XNSIM
    AE1A1=SME1A1/XNSIM
    AE1B11=SME1B11/XNSIM
    AE1B22=SME1B22/XNSIM
    AE1B44=SME1B44/XNSIM
    AE1B12=SME1B12/XNSIM
    AE1B14=SME1B14/XNSIM
    AE1B24=SME1B24/XNSIM
    AE2A2=SME2A2/XNSIM
    AE2A1=SME2A1/XNSIM
    AE2B11=SME2B11/XNSIM
    AE2B22=SME2B22/XNSIM
    AE2B44=SME2B44/XNSIM
    AE2B12=SME2B12/XNSIM
    AE2B14=SME2B14/XNSIM
    AE2B24=SME2B24/XNSIM
    AE3A2=SME3A2/XNSIM
    AE3A1=SME3A1/XNSIM
    AE3B11=SME3B11/XNSIM
    AE3B22=SME3B22/XNSIM
    AE3B44=SME3B44/XNSIM
    AE3B12=SME3B12/XNSIM
    AE3B14=SME3B14/XNSIM
    AE3B24=SME3B24/XNSIM
END IF

C

DO 2 K=1,NIV
Z=DATA (I,J,21+K)
F1STAR(I,J,K,1)=AEE1A1*Z
F1STAR(I,J,K,2)=AEE1A2*Z
C
F1STAR(I,J,K,2)=AEE1A4*Z
F1STAR(I,J,K,3)=AEE1B11*Z
F1STAR(I,J,K,4)=AEE1B22*Z
F1STAR(I,J,K,5)=AEE1B44*Z
F1STAR(I,J,K,6)=AEE1B12*Z
F1STAR(I,J,K,7)=AEE1B14*Z
F1STAR(I,J,K,8)=AEE1B24*Z
F2STAR(I,J,K,1)=AE2A1*Z
F2STAR(I,J,K,2)=AE2A2*Z
C  F2STAR(I,J,K,2)=AE2A4*Z
F2STAR(I,J,K,3)=AE2B11*Z
F2STAR(I,J,K,4)=AE2B22*Z
F2STAR(I,J,K,5)=AE2B44*Z
F2STAR(I,J,K,6)=AE2B12*Z
F2STAR(I,J,K,7)=AE2B14*Z
F2STAR(I,J,K,8)=AE2B24*Z
F3STAR(I,J,K,1)=AE3A1*Z
F3STAR(I,J,K,2)=AE3A2*Z
C  F3STAR(I,J,K,2)=AE3A4*Z
F3STAR(I,J,K,3)=AE3B11*Z
F3STAR(I,J,K,4)=AE3B22*Z
F3STAR(I,J,K,5)=AE3B44*Z
F3STAR(I,J,K,6)=AE3B12*Z
F3STAR(I,J,K,7)=AE3B14*Z
F3STAR(I,J,K,8)=AE3B24*Z
C  PRINT 9998, I,J,K,INTNO,YR,EE1A1,F1STAR(I,J,K,1),F1(I,J,K)
  2 CONTINUE
222 CONTINUE
REWIND 19
9998 FORMAT(2X,3I4,2X,5E13.5,/,12X,5E13.5)
C
DO 55 L=1,NP
  DO 55 K=1,NIV
  DO 55 I=1,NOB
    ASTSUM=0.0
    BSTSUM=0.0
    CSTSUM=0.0
    DO 44 J=1,NTIME
      ASTSUM=ASTSUM+F1STAR(I,J,K,L)
      BSTSUM=BSTSUM+F2STAR(I,J,K,L)
      CSTSUM=CSTSUM+F3STAR(I,J,K,L)
    C  PRINT 9988,L,K,I,J,INTNO,YR,F1STAR(I,J,K,L),ASTSUM
      44 CONTINUE
F1STAR(I,6,K,L)=ASTSUM/XIT
F2STAR(I,6,K,L)=BSTSUM/XIT
F3STAR(I,6,K,L)=CSTSUM/XIT
C  PRINT 9988,L,K,I,J,INTNO,YR,F1STAR(I,J,K,L),ASTSUM,F1STAR(I,6,K,L)
  55 CONTINUE
C
IF(IFLAG1.EQ.1) GOTO 15
9988 FORMAT(2X,4I4,2X,5E13.5,/,12X,5E13.5)
C
C  CALCULATE THE WEIGHTING MATRIX
C
C  THIS JUST SETS THE MATRIX TO AN IDENTITY
DO 21 I=1,1ORTHG
  DO 21 J=1,1ORTHG
    S(I,J)=0.0D0
    IF(I.EQ.J) S(I,J)=1.0D0
  21 CONTINUE
C  LOOP OVER THE COVARIANCE MATRIX CALCULATION
C*******************************************************************************
IF(NOB.GT.0) GOTO 15
C*******************************************************************************
C
DO 17 I=1,IORTHG
DO 17 J=1,IORTHG
ASUM=0.0DO
DO 18 J=1,NOB
IF((I.LE.NIV).AND.(J.LE.NIV)) ASUM=ASUM+F1(JJ,6,I)*F1(JJ,6,J)
IF((I.LE.NIV).AND.(J.GT.NIV).AND.(I.LE.NIVTWO)) ASUM=ASUM+
1 F1(JJ,6,I)*F2(JJ,6,I-NIV)
IF((I.LE.NIV).AND.(J.GT.NIVTWO)) ASUM=ASUM+F1(JJ,6,I)*
1 F3(JJ,6,I-NIVTWO)
1 ASUM=ASUM+F2(JJ,6,I-NIV)*F2(JJ,6,J-NIV)
IF((I.GT.NIV) AND (J.LE.NIVTWO).AND.(J.GT.NIVTWO)) ASUM=ASUM+
1 F2(JJ,6,I-NIV)*F3(JJ,6,J-NIVTWO)
IF((I.GT.NIVTWO).AND.(J.GT.NIVTWO)) ASUM=ASUM+F3(JJ,6,I-NIVTWO)*
1 F3(JJ,6,J-NIVTWO)
18 CONTINUE
17 S(I,J)=ASUM*XNOB
DO 19 I=1,IORTHG
DO 19 J=1,1
19 S(I,J)=S(I,J)
C
CALL INVERT(S,IORTHG,IORTHG)
C
15 CONTINUE
C   END OF WEIGHTING MATRIX CALCULATION
C
DO 77 L=1,NP
DO 77 K=1,NIV
ASTSUM=0.0
BSTSUM=0.0
CSTSUM=0.0
DO 66 I=1,NOB
ASTSUM=ASTSUM+F1STAR(I,6,K,L)
BSTSUM=BSTSUM+F2STAR(I,6,K,L)
CSTSUM=CSTSUM+F3STAR(I,6,K,L)
66 CONTINUE
F11STAR(K,L)=ASTSUM
F22STAR(K,L)=BSTSUM
F33STAR(K,L)=CSTSUM
C
PRINT 7778, K,L, F33STAR(K,L)
77 CONTINUE
C
DO 88 L=1,NP
DO 88 K=1,IORTHG
IF((K.LE.NIV) DER(K,L)=2*F11STAR(K,L)
IF((K.GT.NIV).AND.(K.LE.NIVTWO)) DER(K,L)=2*F22STAR(K-NIV,L)
IF((K.GT.NIVTWO).AND.(K.LE.NIVTHRE))
1 DER(K,L)=2*F33STAR(K-NIVTWO,L)
PRINT 7778, K,L, DER(K,L)
88 CONTINUE
DO 7777 I=1,IERTHG
   DO 7777 J=1,IERTHG
C   PRINT 7778, I,J,S(I,J)
7777 CONTINUE
7778 FORMAT(5X,2I4,3E13.5)
C   C
   DO 10 I=1,NP
   DO 10 J=1,IERTHG
      ASUM=0.0
C   PRINT 7778, I, ORTHOG(I)
   DO 11 K=1,IERTHG
C   PRINT 7778, I,K, S(I,K)
11 ASUM=ASUM+DER(K,1)*S(I,K)
   DS(I,J)=ASUM
C   PRINT 8888, I, DS(I,J), DER(J,I)
10 CONTINUE
8888 FORMAT(2X,2I4,2X,2E13.5)
   DO 12 I=1,NP
   DO 12 J=1,NP
      ASUM=0.0
   DO 13 K=1,IERTHG
13 ASUM=ASUM+DS(I,K)*DER(K,1)
12 DSD(I,J)=ASUM
   CALL INVERT(DSD,NP,8)
   DO 157 L=1,8
      TSTAT=BB(L)/DSQRT(DSD(L,L))
      PRINT 9999,L,SB(L),TSTAT,DSD(L,L)
9999 FORMAT(2X,2I4,2X,2E13.5,/,12X,5E13.5)
C   PRINT 7778, L, FP(L)
157 CONTINUE
9923 CONTINUE
   RETURN
END