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The Returns to Criminal Capital

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The Returns to Criminal Capital

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ABSTRACT

Human capital theory (Becker 1962; Mincer 1958; Schultz 1960; 1961) posits that individuals can increase their labor market returns through investments in education and training. This concept has been studied extensively across several disciplines. An analog concept of criminal capital, while the focus of speculation and limited empirical study, remains considerably less developed theoretically and methodologically. This paper offers a formal theoretical model of criminal capital indicators and tests for greater illegal wage returns using a sample of serious adolescent offenders, many of whom participate in illegal income-generating activities. Our results reveal that, consistent with human capital theory, there are important illegal wage premiums associated with investments in criminal capital, notably an increasing but declining marginal return to experience and a premium for specialization. Further, as in studies of legal labor markets, we find strong evidence that, if left unaccounted for, non-random sample selection causes severe bias in models of illegal wages. Theoretical and practical implications of these results, along with directions for future research, are discussed.

KEYWORDS: criminal capital, illegal earnings, sample selection, Heckman correction

INTRODUCTION

A half a century ago, the economist Gary Becker (1962: 9) noted the importance of “activities that influence future real income through embedded resources in people,” or what is typically referred to as *human capital*. The notion that individuals can generate positive outcomes such as higher earnings through investment in activities including education and training has made the study of human capital a longstanding and widespread source of inquiry in economics, sociology and education. For instance, estimating the return to personal investments in education has been studied extensively in empirical economics. Beyond their theoretical importance, these studies frequently generate popular interest and contentious debates.¹

The theory of human capital has also been considered in criminological discourse. However, unlike its conventional counterpart, theoretical and empirical development of an analog concept of *criminal capital* has been limited.² Several ethnographic accounts of criminal careers illustrate that the accumulation of criminal skills undergoes a process very similar to conventional human capital (e.g., Klockars 1974; Letkemann 1973; Sutherland 1937). Since these important ethnographies, however, interest in criminal capital shifted from explaining the process of accumulating criminal skills and experience to explaining variations in the returns to crime (e.g., McCarthy and Hagan 2001; Matsueda et al. 1992; Morselli et al. 2006; Nguyen and Bouchard 2012; Uggen and Thompson 2003), resulting in a gap in the theoretical and empirical development of a more comprehensive concept of criminal capital.

Unfortunately, this gap in the criminal capital literature is not without consequence. The relationship between indicia of criminal capital and its monetary returns have not been examined in the same detail as conventional human capital, making it premature to make connections between the two. Further, studies that explore variation in criminal earnings have found a

substantial positive effect between indicators of criminal capital and aggregate criminal earnings (McCarthy and Hagan 2001; Uggen and Thompson 2003). But these studies have not adequately accounted for key methodological obstacles which often arise in the study of labor markets. As a result, these studies have produced potentially inconsistent estimates that substantially reduce generalizability.

Information regarding the factors that contribute to criminal success is an important, underexplored avenue for both theory and policy. Even though empirical support for the relationship between the threat of (objective) sanctions and crime is relatively weak (Nagin 1998), the association between perceived rewards and crime is consistently positive and strong, regardless of offense type or offender (e.g., Cornish and Clarke 1986; Paternoster and Simpson 1993; Loughran, Paternoster and Weiss 2012; Piliavin, Thornton, Gartner, and Matseuda 1986). This suggests that individuals appear to be highly responsive to rewards from crime. Stated differently, illegal rewards may have a positive impact on offending frequency and overall criminal career length. Both Shover and Thompson (1992) and Sommers, Baskin, and Fagan (1994) found that the probability of desistance increases when offenders' expectations for achieving rewards from criminal activity decline (see also Giordano, Cernkovich, and Rudolph 2002; Laub and Sampson 2003; Paternoster and Bushway 2009; Pezzin 1995; Shover and Thompson 1986).

The importance of understanding criminal capital, coupled with its relatively few empirical studies, animates the present study. Guided by classical human capital theory, this paper attempts to develop a more robust theory of criminal capital by considering the nature of illegal earnings and how certain criminal productivity indicators might yield higher returns in the illegal labor market. We then test these indicators on a sample of serious adolescent offenders,

some of whom earn income illegally. Our results suggest that criminal capital is analogous to human capital: greater investment in criminal capital results in significantly higher illegal wage rates. Finally, we present strong evidence that, as is well established in the case of legal labor supply, studies of illegal earnings suffer from important sample selection issues which must be properly addressed to produce useful estimates on illegal returns.

Human Capital Theory

Human capital theory posits that individuals and society derive economic benefits from investments that produce “changes in persons that bring about skills and capabilities that make them able to act in new ways” (Coleman 1988: S100). Human capital then, is an intangible stock of skills and knowledge and facilitates productive activity. Although investment in human capital can include a variety of activities, such as health and nutrition (Shultz 1981), the most salient forms of investment in human capital are through education, including investments in formal schooling (Mincer 1974), informal education (Schultz 1981), and both general and specific on-the-job training that increases workers’ skills (Becker 1962). Human capital has a rich history of theoretical and empirical development, demonstrated through the impressive amount of scholarship devoted to its study (see Altonji et al. 2012).

Mincer (1958), Schultz (1960, 1961) and Becker (1962) have each made seminal contributions to human capital theory and the notion that investment in human capital is an inseparable part of an individual, which positively affects wages that an individual can earn. In his influential piece “Investment in Human Beings”, Schultz (1961) argued that estimating the magnitude of human investment is not a straightforward task because qualities such as skills, knowledge and similar attributes are considered both consumption and investment, thereby posing conceptual difficulties and identification challenges. For example, there is an opportunity

cost for obtaining a formal education since individuals must forgo earnings while at school or when participating in on-the-job-training. Given these factors, Shultz (1961) argued that the best way to quantify human investment is by its yield rather than by its cost. That is, the most efficient way to measure human capital is through the increase in one's earnings.

Mincer (1974) developed a basic function of the returns to education, known as the Mincerian function, which fits a function of log-wages by using years of schooling, years of labor market experience and its square as independent variables to determine the average rate of return of schooling and experience. According to Mincer (1974: 287), "as more skill and experience are acquired with the passage of time, earnings rise." One of the key results highlighted by Mincer is that the relationship between experience and wages does not rise linearly—rather it follows an age-earnings profile where experience increases wage rates at a marginally decreasing rate. Hundreds of empirical studies have found support for the Mincer earnings function both in the United States and in other industrialized societies (Borjas 1996; Willis 1986).

Becker (1962) is often credited for the popularization of the idea of human capital and his ideas play an especially important role in the current study. In his treatment of human capital theory, Becker differentiated between on-the-job training through two different types of training: general and specific. Generalized training provides useful knowledge and skills that can be applied to various jobs. Specific on-the-job training is firm specific and tends to provide a greater rate of return only at the particular firm, whereas investment in general training provides less of a rate of return but is a transportable stock of knowledge and skills.

In sum, several fundamental features of human capital theory should be considered before researchers can begin to draw a parallel between human capital and criminal capital. First,

human capital theory argues that investment in education is best captured by an increase in the rate of return. To be clear, specifying a wage rate rather than aggregate earnings in a period provides a more informative measure of the returns to human capital. Second, the relationship between experience and wages is nonlinear—there are diminishing returns to experience.³ Third, the main avenue of investment in human capital is through education, which can take various forms, exemplified by Becker’s (1962) important distinction between investments in general and specific training. Investment in both general and specific training should increase earnings; however, specific training will have greater returns for the particular job.

Is there Criminal Capital?

Does a criminal analog to human capital exist? McCarthy and Hagan (1995) first coined the term “criminal capital” and mirror the definition of human capital. Inspired by Schultz (1961) and Becker (1964), McCarthy and Hagan (1995: 66) define criminal capital as: “a type of human capital...[that] includes knowledge and that can facilitate successful criminal activity”. Using a sample of homeless adolescents from several cities in Canada, they argue that crime-specific tutelage relationships facilitate criminal skills and attitudes, which increases the frequency of drug selling and theft. While they do not directly consider monetary returns, they set the conceptual groundwork for the idea that investment in criminal training can be beneficial.

Others have elaborated the concept of criminal capital and its potential parallels with human capital showing that the accumulation of criminal capital likely undergoes a process similar to the accumulation of human capital. For example, Shover (1996:66) looked at the criminal careers of persistent thieves and observed that “the knowledge and skills needed to earn a good living from stealing probably do not greatly differ from those required for successful legitimate employment”. A handful of other ethnographic studies illustrate that training and time

go into the development of skills in thievery (Sutherland 1937; Steffensmeier and Ulmer 2005), hustling and fencing (Klockars 1974), drug dealing (Fagan 1992; Williams 1989; Jacobs 1996), and burglary (Wright and Decker 1994).

Similar to human capital, criminal specialization appears to have important effects on criminal outcomes. A series of studies on offender decision-making have found that some offenders possess specialized cognitive abilities. For example, Wright, Logie, and Decker (1995), using an experimental design, showed that active residential burglars outperformed a control group when given photos of residential dwellings and asked to recall details of the dwelling and its surrounding areas (see also Carroll and Weaver 1986; Nee and Meenaghan 2006; Wright and Logie 1988; Logie, Wright, and Decker 1992). The value of specialized skills has been highlighted by a number of criminologists (e.g., Cloward and Ohlin 1960; Decker et al. 1993; Shover 1996; Sutherland 1937; Topalli 2005; Shaw, 1930); yet few have investigated the returns to specialization (McCarthy and Hagan 2001).

In addition to ethnographic accounts and a few experimental studies, several studies have attempted to model the relationship between criminal capital and returns from crime. These studies have conceptualized criminal capital in fairly consistent terms. They tend to show that measures such as criminal experience, specialization and tutelage are positive and significant predictors of greater aggregate illegal earnings (e.g., Morselli, Tremblay and McCarthy 2006; Nguyen and Bouchard 2012; Uggen and Thompson 2003). For example, using data from the National Supported Demonstration Work Project, Uggen and Thompson (2003) measured criminal experience by the total number of times the offender was arrested in the 36-month study period. They also included a quadratic arrest term, as, guided by human capital theory, positing that there should be diminishing returns to criminal experience. Uggen and Thompson (2003)

found that there was a significant curvilinear relationship between their proxy for criminal experience and total monthly illegal earnings.

There are several mechanisms through which offenders can accumulate criminal capital. Sutherland (1937; 1947) shows the importance of differential association in his interviews with a professional thief. Sutherland (1947: 6) argued that, through intimate personal ties or networks, “When criminal behavior is learned, the learning includes (a) techniques of committing the crime, which are sometimes very simple; (b) the specific direction of motives, drives, rationalizations, and attitudes”. Akers (1973) extended the notion of differential association in his social learning theory to argue that people acquire and maintain behavior through differential reinforcement contingencies (rewards and punishments); imitation or modeling others’ behavior; and through definitions, which are expressions of values and norms. In addition to providing models, training and reinforcements for criminal behaviors, peers can be valuable sources of information and opportunity that can make the returns to criminal capital greater (see Cloward and Ohlin 1960; Osgood et al. 1996; Stafford and Warr 1993; Warr 2002; for a discussion on various mechanisms of peer influence). Finally, Bayer, Hjalmarsson and Pozen (2009) explicitly hypothesized that an individual can build criminal capital while in correctional facilities. They found that increased exposure to peers with a history of a specific crime type increases the likelihood that the subject (who has already committed that crime type) will commit that particular crime type upon release. Their conceptualization of criminal capital is considerably broader and is more akin to a peer influence perspective rather than a traditional human capital orientation.

Differences between Criminal Capital and Human Capital

Although human capital theory provides a useful theoretical point of departure for exploring the concept of criminal capital, a closer comparison reveals a number of ways these concepts diverge. First, while both human capital and criminal capital are grounded in a rational choice framework (Becker 1968), the former is necessarily steeped in the concept of a future-oriented agent.⁴ Human capital theorists argue that one way to measure human capital at the individual level is through a cost-based approach that considers both investment costs and discounted income in the future (Kendric 1976; Jorgenson and Fraumeni 1989). This method represents the familiar notion of delayed gratification on the part of the individual investing in human capital. In the extensive literature on legal labor supply and rational choice, economists have articulated a range of concepts pertaining to agents making decisions in the context of the life cycle, including intertemporal substitution effects between work and leisure (e.g., Altonji 1986), preferences for increasing wage profiles (Lowenstein and Sicherman 1991), and rational expectations regarding future earnings (Muth 1961). Accordingly, there is strong theoretical and empirical evidence to suspect that legal earnings reflect optimal investment in human capital over the life cycle (Ben-Porath 1967).

Conversely, in the criminal realm, it is unclear if there is a related delayed gratification process or consideration of discounted future income. In fact, in direct contrast to economic theories of time which assert in one form or another that current period behavior is tied to expectations of future earnings, many criminal investments are more likely motivated by a heightened sense of present-orientation (Gottfredson and Hirschi 1990) or hyperbolic time preference. More specifically, illegal market entry decisions are more likely to be driven by the immediacy of criminal gains, as compared to legal earnings that are usually delayed. Laub and

Sampson (2003:179) for example, describe the influence of “fast money” as motivation for persistent offending in certain individuals.

Furthermore, criminal earnings are almost certainly more transitory than legal earnings. The temporary status of criminal wages can cloud future expectations of illegal earnings and introduce instability into decision making. This inconsistency suggests that the models of illegal labor supply and criminal capital, while sharing some similarities to human capital and wages, could lead to quite different legal supply models—specifically, illegal entry decisions are perhaps a function of *both* immediate illegal and discounted (or foregone) legal incentives. Indeed, some descriptive evidence suggests that legal work and illegal work are not always seen as trade-offs (Fagan 1992; Freeman 1996; Reuter et al. 1990; Viscusi 1986).⁵ This also implies that to measure criminal capital, one must rely on the alternative income-based approach, as opposed to cost-based, which measures human capital through productivity measures, i.e., its rate of return (Shultz 1961; Mincer 1974).

A second, more fundamental distinction between human capital and criminal capital is the role that social capital plays in acquisition and returns. Social capital, or resources embedded in a social structure that can facilitate action, was largely neglected in the conceptualization of traditional human capital theory (Coleman 1988). Coleman argued that the traditional world view of human capital was an under-socialized view and suggested that social structure could be incorporated in the economists’ principle of rationality. He noted that just as “human capital can facilitate productive activity, social capital does as well” (S101). For example, groups that have trust among its members are able to accomplish more than groups that have less levels of trust. Similarly, Granovetter (1985) criticized a pure market approach to economic action and

highlighted the importance of social structure in the economic analysis of human behavior. It is within social networks that most economic actions take place (see also McCarthy 2002).

Social capital can exist in several different forms. It can be a collective resource that can facilitate mutual trust and informal social control (e.g., Sampson et al. 1999; Skogan 1990) or produce civic engagement (Putnam 2006). Alternatively, other scholars such as Bourdieu (1986), Burt (1992), and Lin (1999) illustrate how individuals instrumentally develop and mobilize social ties to secure their goals. Both forms of social capital can contribute to greater earnings.

One of the most compelling demonstrations of the importance of social capital is in migrant communities. Several scholars underscore the importance of social capital in migration efforts (Massey and Aysa 2011; Garip 2008) and prosperous entrepreneurship in studies of the immigrant and ethnic entrepreneurship (Aguilera 2005; Zhou and Logan 1989). Through community networks, members of immigrant communities have access to information, start-up financial capital, and a pool of dedicated labor supply (Portes and Sensenbrenner 1993). Similar to this reliance on informal exchanges and trust, social capital also contributes to prosperity and cohesion among criminal networks (Browning et al. 2004; Portes 1998). In addition to facilitating the accumulation of criminal capital, social capital facilitates obtaining greater returns to criminal capital.⁶

Human capital can be accumulated from social capital; however, criminal capital is arguably *more* reliant on criminal social capital because of the informal social nature of most criminal enterprises. For instance, unlike legal labor markets, the illicit economy has no formal “schools of crime” to facilitate the acquisition of criminal skills or knowledge nor are there formal avenues to advertise or disseminate knowledge. Much of the transmission of criminal skills takes place through informal social networks rather than structured opportunities,

economies or institutions. Castells and Portes (1989) draw distinctions between formal and informal economies to argue that the differences lie not in the goods themselves but in the manner in which goods are exchanged in the absence of state regulations, as the informal economy is dependent on social ties, trust, and mutual obligations for effective functioning (see also Portes and Haller 2005). Therefore, it is likely that embeddedness, or ongoing social relations, in criminal social networks plays a crucial role in both investment in and returns to criminal capital. Indeed, prior studies have shown that criminal embeddedness positively contributes to greater illegal earnings (e.g., Levitt and Venatesh 2000; Morselli et al. 2006; McCarthy and Hagan 2001).

These studies suggest that intertemporal investments and measurements imply important differences between human capital and criminal capital. More important, while traditional human capital theory inherently and necessarily draws attention to the individual and her position relative to social and economic institutions, this strictly individualistic view of human capital only partially translates to the complex intersection of social structural and individual factors that shape the tangible returns to criminal capital. We elaborate these concerns in our theoretical specification in the sections that follow.

THE PRESENT STUDY

The current study builds on previous work in several ways. First, we simultaneously consider multiple measures of criminal capital, designed to capture both general and specific experience, using a sample of serious adolescent offenders for whom we observe detailed information about illegal wage and participation activity. Second, unlike previous studies of illegal wage functions that consider total wage volume, we model the outcome of wage *rates* to capture criminal productivity returns. We hypothesize that a participants' wage rate will increase

as their criminal capital indicators rise, and specifically with respect to experience, this increase will occur at a marginally declining rate. Third, we address the problem of sample selectivity bias in estimating the returns to our criminal capital indicators, and attempt to correct for it using multiple strategies. We initially consider the classic, widely used solution offered by Heckman (1979)—a two-equation model where selection can be treated as a form of omitted variable bias. Though this estimator is sometimes criticized for over-sensitivity to distributional and functional form assumptions, as well as general misuse in criminological research (Bushway et al. 2007), the strength of our results rests on our usage of multiple exclusion restrictions (i.e., variables which are important to explain selection, but given productivity characteristics, do not explain illegal wage rates), which mitigate these concerns. Further, we exploit the fact that our data reveals more about the individual selection process beyond the binary participation choice, namely the total amount of time engaged in illegal income-generating activities. This allows us to modify the standard Heckman estimator and reduces the reliance on the nonlinearity assumptions in the standard model.

The remainder of this paper is organized as follows. The next section describes the data and provides descriptive statistics of our criminal capital indicators and illegal wages. This is followed by a description of our model of the returns to criminal capital, a discussion of the problem of sample selectivity, and the empirical strategies employed to consistently estimate the model parameters. We then present the results. We conclude with a discussion of the findings and implications for subsequent research.

DATA

We analyze data from the Pathways to Desistance study, a longitudinal investigation of the transition from adolescence to young adulthood in serious adolescent offenders. Study

participants are adolescents who were found guilty of a serious offense (almost entirely felony offenses) in the juvenile or adult court systems in Maricopa County (Phoenix), AZ or Philadelphia County, PA. These youth were ages 14 to 17 at the time of enrollment into the study (M = 16.5). A total of 1,354 adolescents are enrolled in the study, representing approximately one in three adolescents adjudicated on the enumerated charges in each locale during the recruitment period (November, 2000 through January, 2003).⁷ The study sample is comprised mainly of non-white (44% African American, 29% Hispanic) males (86%), who were, on average, 14.9 years old at the age of their first petition, with an average of three petitions prior to the baseline interview.

In this analysis, we use data collected at six consecutive follow-up interviews corresponding to six-month observational periods over 36 months for a total pooled sample of $N=7,399$ (which represents over 91% retention). As described below, not every individual reports involvement in illegal income-generating activity in all periods (this is the selection problem). In each period, we observe for each individual the number and types of income-generating crimes they report committing, if any, during the observation period, along with their age, income risk perceptions, and drug dependency. In addition, detailed information regarding the number of continuously measured weeks in which participants were engaged in both legal and illegal activities and the total amount of money earned from each activity each month were recorded by using a life-event calendar that subjects completed as part of the interview. This information was aggregated to provide earnings and employment information for each of the follow-up periods. Also, the life history calendar allows us to determine the proportion of time each individual was not locked up in a secure facility (exposure time). Methods for constructing life-event calendars have been shown to be reliable in studies of criminal offending, antisocial,

and mental health service use (Caspi et al. 1996; Horney, Osgood, and Marshall 1995; Morris and Slocum 2010; Roberts and Horney 2010).

Outcome Variable

Illegal wage rate. The illegal wage rate was calculated by dividing an individual's total reported illegal earnings in a month (based on the calendar) by the total number of weeks worked across all illegal jobs. The number of weeks were calculated by multiplying each week the participant worked by 1.3 to account for the fact that all months are not exactly four weeks long (52 weeks in a year / 12 months in a year = 4.333 weeks per month) and summed across all types of illegal work in the recall period.⁸

In total, 496 individuals out of the 1,354 total sample report earning illegal wages in at least one period (~37%). Of these 496, more than half only report earning illegal wages in one period (n=265). Pooling all of the individual observations together yields a total sample size of $N=883$ observations of illegal wage rates (out of a total pooled sample of $N=7,399$). Due to missing data issues detailed below, our select sample is reduced to $N=833$ for model estimation. As is standard in wage models, we take the natural log of illegal wage rate to use as the dependent variable which helps deal with the skewness of the measure. Histograms of both the untransformed and transformed rates are displayed in Figure 1. We explore a descriptive summary of this outcome in more detail below.

* Figure 1 about here *

Criminal Capital Measures

Criminal experience. We measure criminal experience as the individual's cumulative frequency of participation in illegal income-generating activities in each period. The number of crimes an individual commits is derived from their self-reported offenses (SRO) recorded in each

period. This measure is a revised version of a common self-reported delinquency measure of the number of crimes committed (Huizinga et al. 1991). We trim this scale to include only the 10 income-generating offenses (thus eliminating aggressive crimes which do not have a direct relationship with illegal wages).⁹ In each period, an individual is asked whether they committed each of these 10 crimes in the past 6 months, and if so, how many times. These values are then summed to arrive at a total period frequency and then cumulative frequency. Therefore, our measure of experience provides a cumulative measure of general experience with income-generating crimes.

Because cumulative income frequency is skewed, we created a vector of categorical experience variables using the quartiles of the conditional distribution of cumulative frequency based on participation. The lowest category was then subdivided in two in order to better capture variation among non-participants. This yields five unique experience categories: low (0-2 cumulative crimes reported), moderate (3-20 crimes), high (21-110 crimes), very high (111-213 crimes), and extreme (> 213 crimes). Beyond simply dealing with the skew problem, this categorical strategy allows us great flexibility in detecting potential nonlinear marginal returns to criminal experience, as is the case with diminishing marginal returns to experience in human capital.¹⁰

Of the original $N=883$ observations, 88 cases (9.9%) had missing interview data in at least one time point prior to the relevant period, meaning we could not observe offending frequency for the missed period. Thus, we were unable to calculate a total cumulative frequency score. Of these 88 cases, we could safely conclude that 38 of them fell into the extreme category based on observed experience which already exceeded the top threshold regardless of the missing values. To use the remaining 50 cases, however, would have required us to make an

untestable assumption about the nature of the missingness. Therefore, we dropped these cases to bring our estimation sample to $N=833$.¹¹

Specialization. Here we consider the unique number of crime types reported by an individual in the observation period and generate an indicator equal to 1 if the individual reports engaging in two or fewer unique crime *types* during the observation period and 0 else. We define specialization as two or fewer instead of one or fewer since there are certain pairs of crimes which are natural compliments (i.e., stealing and selling stolen goods).¹² Over one-half (56.7%) of individuals reporting illegal wages were specialized. Also, importantly, there was variability in specialization among non-market participants (or else it would be a perfect predictor of participation). This is plausible as some individuals engage in crimes like stealing but do not generate monetary earnings from the activities.

Criminal embeddedness. We measure embeddedness in a criminal social network through the degree of peer delinquent behavior, a subset of similar measures used in the Rochester Youth Study (Thornberry et al. 1994). According to Hagan (1993), criminal embeddedness involves connections to delinquent peers as an indicator of opportunity structure. Hagan used a similar measure of criminal contacts as did Granovetter (1985) in his discussion of employment contacts. It is also probable that, through the context of social learning theory (Akers, 1973), embeddedness functions as an indicator of learning and training in illegal skills. An individual's score is computed as the mean rating of the prevalence of friends who engage in 12 types of delinquent behavior (e.g., 'How many of your friends have sold drugs?'). The subscales had very high internal consistency ($\alpha = .93$).¹³

Panel A of Table 1 reports descriptive statistics for the two criminal capital/productivity measures as well as embeddedness. Importantly, notice the distribution of experience in terms of

total frequency is very different between the select sample and non-earners. Finally, we note that for all three variables, there are important mean differences in each of the indicators between illegal wage earners and non-earners (all p -values $< .001$).

* Table 1 about here *

MODEL

We wish to estimate the parameters of the following illegal wage rate function, specified as an analog to a traditional Mincer equation:

$$\ln(iw_i) = \beta_0 + \beta_1 \text{exp}_i + \beta_2 \text{spec}_i + \beta_3 \text{embed}_i + \varepsilon_i \quad [\text{Eq. 1}]$$

where $\ln(iw_i)$ is the natural log of the rate of weekly illegal earnings an individual reports, *exp*, *spec* and *embed* are our measures of criminal experience, specialization and criminal embeddedness, respectively, and their coefficients can be thought of as the returns to these criminal capital/productivity indicators. If we could observe the illegal wage offer for every individual in the sample, then the model parameters could be estimated simply by using Ordinary Least Squares (OLS). However, we are challenged by a key methodological issue that pervades all empirical earnings research—sample selectivity, which will require an alternative estimation strategy to produce consistent estimates.

The Problem of Sample Selectivity in Modeling Illegal Wages

Illegal wage data suffer from a problem known as incidental truncation, or a type of sample selection which occurs when we only observe one variable (illegal wage rate) based on another variable (participation in the illegal market).¹⁴ We only observe the illegal wage offer for individuals who participate in illegal markets; otherwise, their wage offer is unobservable. Furthermore, it is very likely that the selection mechanism is endogenous. OLS in this case will

yield biased estimates of the true model parameters, i.e., those which are generalizable to the population of serious adolescent offenders, the sample being considered in the current study.

This complication is also a direct analog to another standard problem in labor economics—modeling a wage offer based on labor force participation, first considered by Gronau (1974). Ideally a rate of return to investment in education, for example, should be based on a representative sample of the population. Gronau’s model of labor supply implies that an individual will only choose to participate in the labor market if the wage offered is greater than the ratio of the (negative) marginal disutility of working to the marginal utility of income, a quantity known as one’s *reservation wage*. Intuitively, a reservation wage is the lowest wage rate for which a worker is willing to accept a job. The higher one’s reservation wage, the less likely they are to enter the market *ceteris paribus*. A common occurrence is in the study of female labor supply (Heckman 1974), where the wage offer is observed only for women who choose to enter the labor market, a nonrandom subsample of the population. Therefore, estimates of returns to productivity characteristics for this subsample will be biased estimates for the entire population. The identification issue in the context of sample selection has been discussed by various scholars (see Berk 1983; Heckman and Robb 1986; Bushway et al. 2007).

To our knowledge, there is only one study on illegal earnings that addresses issues of sample selection. McCarthy and Hagan (2001) explore whether specialization in drug selling is associated with greater returns. McCarthy and Hagan first use a probit model to estimate the probability of participating in drug selling in the first wave, and then employ a tobit model to assess drug selling income in the second wave. However, this strategy essentially treats the zeros as being censored—which is unrealistic—as opposed to being unobserved due to selection. Furthermore, this does not allow for an examination of the magnitude of the bias which would

have occurred had the problem been ignored altogether. In sum, sample selection issues likely plague studies of illegal wages, which if ignored, will lead to biased estimates. Unfortunately, very few studies have adequately considered this issue, making previous estimates on criminal capital indicators difficult to generalize.

The problem of incidental truncation requires us to use an estimator designed to correct for sample selectivity bias. To employ Heckman's (1979) estimator and variations of it, we must observe the productivity characteristics for both illegal market participants and non-participants in the sample, even though we cannot observe the wage offer for the latter.

Dealing with sample selection requires a second, selection equation:

$$s_i = 1 \cdot [\delta \mathbf{z}_i + v_i > 0] \quad \text{[Eq. 2]}$$

where $1 \cdot []$ denotes a binary indicator function, $s_i = 1$ if the individual participates in an illegal income-generating activity during the observation period and 0 else, and \mathbf{z}_i is a vector which includes all of the regressors in eq. 1, as well as variables which, by assumption, are predictive of selection into illegal market participation, but given one's capital/productivity characteristics, have no impact on the wage offer. These assumptions are known as *exclusion restrictions*, since they are excluded from the wage equation, and they are crucial for identification of the model parameters. We return to them shortly.

The Heckman model assumes that the error terms, ε_i and v_i , are jointly normally distributed each with mean zero and correlation ρ . Under the null hypothesis $H_0: \rho = 0$, selection is exogenous and eq. 1 can be consistently estimated using OLS. Rejection of H_0 implies a selection problem, and we will need to correct for it.¹⁵ The parameters in eq. 1 can then be consistently estimated by first estimating eq. 2 using probit, and then use these first stage

estimates to calculate the inverse Mills ratio, $\lambda(\delta\mathbf{z}_i)$, for each individual.¹⁶ This term can be included as an additional regressor in eq. 1, which yields the following conditional expectation:

$$E[\ln(iw_i) \mid s_i = 1, exp_i, spec_i, embed_i] = \beta_0 + \beta_1 exp_i + \beta_2 spec_i + \beta_3 embed_i + \rho_{\varepsilon, \nu} \sigma_{\varepsilon} \lambda(\delta\mathbf{z}_i) \quad [\text{Eq. 3}]$$

Written this way, one can see how the omission of the λ term, which contains elements of \mathbf{z} , would result in an omitted variable bias, which OLS can ‘correct’ for once we include this term. The model can be estimated using a full maximum likelihood (ML) procedure, which by accounting for the λ term will yield consistent estimates of the β parameters.¹⁷ This procedure will also provide estimates of the selection equation δ parameters from eq. 2 via probit, as well as estimates of ρ and σ_{ε} (the variance of the error term in the main equation). Notice that the coefficient on the λ term in eq. 3 is $\rho\sigma_{\varepsilon}$, meaning that failure to reject it is equal to zero means either $\sigma_{\varepsilon} = 0$ (which is impossible) or $\rho = 0$, which is the same test of H_0 .

A Tobit Selection Equation

In the case where we have more information available on selected sample beyond binary participation, specifically concerning *level* of participation in the illegal market (e.g., hours, weeks), we can exploit this in selection correction. We still wish to consistently estimate the parameters of eq. 1, but now we may rewrite the selection equation as:

$$h_i = \max(0, \boldsymbol{\pi}\mathbf{z}_i + \eta_i) \quad [\text{Eq. 4}]$$

where h_i is the amount of illegal hours or weeks supplied, $\ln(iw_i)$ is observed only when $h_i > 0$, the vector \mathbf{z} again contains exclusion restrictions and $\boldsymbol{\pi}$ is parameter vector. We make very similar assumptions to the standard Heckman model, except now we allow the error term η_i (again assumed to be normally distributed) to have an unknown variance. Here, we assume the relationship between the main equation error term ε_i and η_i can be written as $E(\varepsilon \mid \eta) =$

$\gamma\eta$, where γ is a parameter to be estimated. Now the selection equation can be estimated by tobit, and using the residuals from this model, the new conditional expectation function becomes:

$$E[\ln(iw_i) | h_i = 1, \eta_i, exp_i, spec_i, embed_i] = \beta_0 + \beta_1 exp_i + \beta_2 spec_i + \beta_3 embed_i + \gamma\eta_i \quad [\text{Eq. 5}]$$

Thus, including the fitted residual values $\hat{\eta}_i$ and using OLS will produce consistent estimates of the β parameters. A rejection of the null hypothesis $H_{0,J}: \gamma = 0$ using the t -statistic from OLS implies there is a sample selection problem (Vella 1998).

Amemiya (1985) refers to this correction procedure as a *type III Tobit* (T3T) model, and the parameters can be estimated by using either ML or a two-step procedure. As explained by Wooldridge (2002), there are two key benefits to using this model over the standard Heckman probit selection estimator. First, since we are using more information in the selection equation this should result in a more efficient estimate. Second, and more importantly, the absence of a valid exclusion restriction is not a problem here, as there will be variation in the tobit residuals just based on variation in the hours variable (as compared to the probit case where the variation would be due entirely to the nonlinearity based on a normality assumption). Therefore, in the case of the failure of our exclusion restrictions, we should still be able to consistently estimate the parameters of interest, although the validity of our exclusion restriction assumptions would be additionally useful.¹⁸

Exclusion Restrictions

Recall that we impose multiple exclusion restrictions on eq. 1, that is, we assume that some variables appear only in the selection equation (i.e., they are included in \mathbf{z}) but not in the wage equation. The assumption here is that, conditioning on the capital/productivity characteristics, the regressors that only appear in the selection equation have no impact on the

wage offer.¹⁹ In the absence of such assumptions, the identification of the model parameters is due entirely to strong functional form assumptions, the failure of which can be highly problematic.²⁰ Here, we consider five variables we argue have proper theoretical justification as joint exclusion restrictions: age, sanction risk perception for income-generating crimes, employment in legal work, drug dependency, and proportion of time during the 6-month interview period the individual was not in a secure detention facility (exposure time).

Age. Age is perhaps the best predictor of crime participation (Farrington 1986; Hirschi and Gottfredson 1983; Steffensmeier et al. 1989), and it is particularly relevant of non-participation (i.e., desistance) in the current sample of serious offending adolescents. Yet, any observed wage premium for older offenders would likely be due strictly to the correlation between age and experience, as opposed to age itself. The subject's age was coded continuously at each follow-up interview. The average age of individuals who reported illegal market participation in the period was 18.31 years, slightly more than the mean of 18.28 years for those individuals who did not participate during a period.

Income risk perception. An offender's subjective risk perception has generally been shown to be negatively associated with offending decisions (Nagin 1998; Piquero et al. 2011), and in particular this association has often been observed more prominently when considering income-generating crimes (Loughran et al. 2011). Specifically, an offender's reservation wage, and by extension his or her participation decision, should be directly related to how much risk is involved in the illegal activity. However, once the decision to participate in an illegal activity has been made, one's own subjective risk perception should have no impact on the returns generated by the activity. Perceived risk is measured in each period by asking respondents how likely it is they would be caught and arrested for the following four crimes related to income-generating

offending: robbery with gun, breaking into a store or home, stealing clothes from a store, and auto theft. Response options ranged from 0 (no chance) to 10 (absolutely certain to be caught). The composite average of the four risk perceptions is then taken as the total measure. The mean risk score of those who report illegal earnings, 5.03, is expectedly lower than the mean for those who do not, 6.15.

Legal employment. Employment in a legal job should be negatively related to illegal market participation, as legitimate employment has consistently been shown to aid in the desistance process (Sampson and Laub 1993; Uggen 2000). Also, Grogger (1998), in an analysis of the National Longitudinal Survey of Youth data, found that increases in legitimate wages reduce participation in crime. Moreover, there is no discernible reason to suspect that involvement in the legal market should influence one's returns from the illegal market. Our measure is an indicator generated from the life event calendar equal to 1 if the individual reports having legitimate legal employment at any time during the observation period, else = 0. Over a third (34.5%) of illegal market participants report legal employment and 39.6% of non-participants did.

Drug dependency. Drug dependency was found to be the most important indicator of illegal wage volume by Uggen and Thompson (2003), suggesting participation in the illegal market is necessary to generate the types of funds needed for drug procurement. It is also likely that additional motivation from the prospect of substance use should lower one's reservation wage. Importantly, Uggen and Thompson's analysis consider *total* monthly illegal earnings, not wage rate. If, for instance, the desire for illegal earnings to purchase drugs increased the amount of time one chose to participate in illegal income-generating activities (which is likely as these individuals would probably have a lower reservation wage), then volume of participation could

explain this result, as opposed to the notion that one's illegal wage rate should be higher for drug users. Subjects were asked to report on several indicia of their drug dependency in each recall period. A total of 10 items was summed into a count variable indicating the severity of dependency symptoms. If the subject answered affirmative to one or more of the symptoms, he/she was considered drug dependent and was coded 1. Subjects who did not report any symptoms of dependency were coded 0. Those who reported involvement in an illegal market reported considerably more drug dependency than those who were not (45.6% vs. 18.4%).

Exposure time. This measure is the proportion of time during the 6-month recall interview period the individual was not in a secure detention facility and was thus on the street. We expect that an individual's exposure time should be positively related to participation purely through increased opportunity. Piquero et al. (2001) demonstrated that individual offending patterns were altered between models that did and did not include controls for exposure time. Beyond this, however, one's exposure time should otherwise have no relation to illegal returns. To calculate, we include only stays in settings without access to the community (e.g., jail/prison; see: Mulvey et al. 2007). Individuals who report illegal market participation during a period have a slightly higher average exposure time than those not in the market (66.2% vs. 64.0%), although the latter group has a much higher standard deviation (.435 vs. .356). Also, note that 14.7% of the observations report an exposure time of 0, meaning they were in an institutional environment for the entire observation period.

We point out that the number of exclusion restrictions is a strength of our analysis, and it means that our model is over-identified. Thus, the failure of any one should not be fatal. Importantly, we tested our model with various specification combinations of fewer restrictions

and found the results to be generally robust. Descriptive statistics for these excluded variables are summarized in Panel B of Table 1.

Finally, we note that in all reported hypothesis tests throughout the remainder of the paper, standard errors are cluster corrected at the individual level. This is important since, as we are using pooled data, the error terms are likely not independent, and without such a correction, the standard errors are underestimated by as much as 30%.

RESULTS

Descriptive Statistics on Illegal Wage Rates

Table 2 reports descriptive statistics for the illegal wage rate outcome. Overall, the mean reported illegal wage (conditional on reporting) rate is \$929/week. To put this number in perspective, the mean reported *legal* wage rate in the sample is \$290/week, or in other words, the mean illegal rate is about 320% higher than the legal rate. This expected premium reflects, among other things, the inherent risks in illegal wage activities as compared to legal wage activities which would increase one's reservation wage. Of course, as is the case with any wage distribution, there is substantial skew (s.d. = \$1,491). Still a comparison of the median rates still reflects a 78% premium for the illegal rate (\$422/week vs. \$245/week). Finally, the interquartile range for the illegal wage rate extends from \$102/week to \$1,000/week suggesting that, beyond just the outliers there is a great deal of variability in wage rates.²¹

* Table 2 about here *

Table 2 also reports how the average wage rate varies with our criminal capital measures. First, notice that the mean wage rate is generally *increasing* as a function of cumulative experience (as shown in Figure 2). More importantly, this relationship also appears to be nonlinear. The mean reported illegal wage rate for the low experience group is \$441/week, while

the mean for the moderate group is almost identical, \$439/week. However, there is a large premium in the rate going from moderate to high experience ($F = 8.28$; $p = .002$), for whom the rate is \$824/week (a 91% increase). Similarly, there is another large increase in wage rate between the high and very high levels of experience ($F = 5.05$; $p = .025$), which increases to \$1,221/week. This represents a 48% increase over the high rate, and a 178% increase over the moderate rate. Finally, there appears to be no premium for the extreme experience group, and in fact the mean wage rate actually *decreases* slightly, although we cannot reject a null of no difference between the very high rate ($F = 0.20$, $p = .655$).²² This set of results suggests that there may be a return to criminal experience in terms of a wage premium, at least once experience exceeds a certain threshold. Yet, there also appears to be a *diminishing marginal return* to experience, which is a perfect analog to the returns to experience predicted by human capital theory.

* Figure 2 about here *

There is also a 24% higher premium ($t = 1.99$, $p = .046$) for the mean rate of those individuals who are specialized (\$1,034/week) as compared to non-specialized (\$834/week). Finally, criminal embeddedness was also strongly and positively related to illegal wage rate ($t = 2.28$, $p = .023$). Specifically, a one standard deviation increase in delinquent peer activity corresponds to a \$127/week increase in mean wage rate.²³

It appears that illegal wage rates are related very strongly to our indicators of criminal capital. We now consider estimating the returns to the measure more rigorously.

Selection into Illegal Income-Generating Participation

Table 3 reports the estimates from the first stage selection equations for both the probit and tobit selection models (eqs. 2 and 4, respectively). First notice that in both models, each of

the excluded regressors has a statistically significant impact on selection, with the lone exception of age in the tobit model (which could be due to the limited age range in the sample). Again, though we cannot explicitly test if our exclusion restrictions are valid, this set of results is highly congruent with our assumptions.²⁴

The signs of the coefficients in all cases are consistent with the theoretical prediction. Individuals with a higher proportion of street time and those engaged in drug use were more likely to select into illegal wage generating activity and participate for more time. Conversely, older individuals, those with legitimate employment, and those with higher risk perceptions for detection were less likely to select into illegal earnings activities and fewer hours or weeks.

* Table 3 about here *

These results from the selection equations strongly support our theoretical predictions and point to a problem of sample selection bias. We next consider the results from the main wage rate equations to test this formally.

The Returns to Criminal Capital

Table 4 reports estimates of the parameters of the main wage equation (eq. 1) generated using pooled OLS, Heckman, and T3T estimation. The OLS results show that when considering all of the criminal capital indicators simultaneously, the returns to each of these indicators is strong and positive. As was the case with the conditional mean wage rates, there appears to be little to no wage premium for moderate experience (relative to the low base category), but returns increase with more experience (the reported F -tests show these incremental changes are statistically significant). Returns level off for the extreme group, again showing the same pattern of increasing (once a certain threshold is passed) but diminishing marginal returns to criminal experience. For instance, the coefficient on the high experience category implies that going from

low to high experience results in a 110% increase in expected illegal wage rate.²⁵ Also, there are wage premiums for both specialization (61% increase) and criminal embeddedness (a one-unit increase in embeddedness corresponds to a 15% increase in wage rate).

* Table 4 about here *

Still, results from both the selection correction models suggest the presence of strong selectivity bias in these prior estimates. In the Heckman model, we can comfortably reject $H_0: \rho = 0$ ($p = .019$). Even stronger evidence comes from the T3T model estimates, where the t -ratio on the fitted residuals term is quite large (-4.43) meaning we can reject $H_{0,I}: \gamma = 0$ ($p < .001$). But the best indicator of selectivity bias is much more intuitive—the coefficients from the two selection correction models, while similar between the two models, differ in magnitude considerably from the OLS estimates. In fact, it appears as if the OLS results on the select sample *severely upwardly bias* the returns to criminal capital indicators. The estimates from the selection corrected models reveal a 76% and 83% reduction in the magnitude of the coefficient on the high group for the Heckman and T3T estimates, respectively. Notice the sign of the estimate actually changes in both cases for the moderate coefficient. For all other model coefficients, there is between a 38%-51% reduction in the magnitude from the OLS point estimate.

In the Heckman and T3T model estimates, there appear to be no returns to either moderate or high experience (in either model there is a small wage premium for high experience, ~14% according to the T3T results, but these estimates fail to approach any conventional level of statistical significance). There are, however, large and statistically significant returns to very high levels of experience (an increase in wage rate of ~112%). Again though, the incremental change from very high to extreme experience is null (although notice that the change in point

estimates is now positive), again suggesting increasing but marginally declining returns to criminal experience. Also, once again this implies the existence of an experience ‘threshold’ before there is a wage rate increase. In terms of a specialization premium, the Heckman and T3T estimates imply increases of 32% and 27%, respectively, in wage rates. A one unit increase in the embeddedness measure yields a small increase return (~8%), although in both models this result is only marginally statically significant. Again, these magnitudes are substantially smaller than the OLS estimates. Finally, note that the estimates both from selection models are generally in close agreement, which is a good robustness check.

In total, these results suggest that, as is the case with human capital indicators, there are increasing but marginally declining returns to criminal experience, a wage premium for specialization, and perhaps a small return associated with criminal embeddedness. Moreover, there are strong selection effects that severely bias OLS estimation of returns to criminal capital.

DISCUSSION

In this paper, we assessed whether it was theoretically and empirically reasonable to draw a direct parallel between human capital and criminal capital. To this end, we considered a number of fundamental theoretical and methodological concepts associated with human capital theory and attempted to mirror them in the criminal realm. In doing so, we attempted to develop a more theoretically and methodologically comprehensive way in which to assess the returns to investments in criminal capital. Among a sample of serious offending adolescents, we found to a certain extent that criminal capital operated similarly to conventional human capital, as it appeared that greater investment in criminal capital productivity characteristics likely yielded greater returns in the illegal activities markets.

Specifically, we found that once a certain experience threshold was passed, there was a large, marginally declining wage premium for experience, a direct analog to results from Mincer earnings equations derived from human capital theory, something that few have considered in the illegal earnings literature. There are a number of reasons why the rate of return to investments decline over time. At higher levels of education, the reward structure tends to be smaller and have less income inequality. Moreover, human capital is most abundant at higher levels and therefore the premium for human capital is not as high (Psacharopoulos 1987; 2006). Similar logic would seemingly apply to the illicit economy, which seems to also have strong market features and where there is likely important competition among certain high volume earners. Future research should continue to explore the illegal earnings experience profile to better determine the point at which the returns to criminal capital begin to decline, as it is an important consideration for policy makers.

We also found important wage premiums for specialization in certain crimes, and to a lesser extent, criminal embeddedness. The premium for embeddedness, even after controlling for experience, implies that there is an important socialization aspect to illegal returns and makes the case for the relevancy of criminal networks. Taken together, these results imply that, through investment in one's own criminal productivity characteristics, an offender can likely earn more through illegal means.

Furthermore, our results revealed strong evidence that bias from sample selectivity, if left unaccounted for, can dramatically affect the inferences one draws about the nature of factors that contribute to illegal earnings. Specifically, using only offenders who report illegal earnings may constitute an endogenously selected subsample of a larger population of interest. We employed standard modeling techniques typically used in empirical labor economics to show that ignoring

such selection biases greatly overstated the magnitudes of the relationships between wages and important predictors. Going forward, we advocate for increased methodological and theoretical rigor borrowed from the rich and very well-developed field of labor economics in the study of illegal wages and labor supply.

Substantively, these findings have important implications for sociological theories of crime. Descriptively, we find large amounts of important variability in the distribution of illegal wage rates, and we note that average wage rates, as well as the amount of variability, are considerably higher for illegal activities as compared to legal jobs. This finding suggests that individuals vary in their ability to earn money from crime. Tremblay and Morselli (2000) explored the idea of an efficiency ratio and found that a small group of offenders have much higher pay-offs per crime than others, though they did not assess the factors that contributed to the higher pay-offs. Our findings suggest that, as in legal work, investment in time, training, and specialization contributes to higher wage rates. This places evidence contrary to Hirschi's (1986: 115-116) contention that "the criminal career does not appear to be one of increasing in skill and sophistication but the reverse, a career that starts with little of either and goes downhill from there". We find that similar to the importance of social networks in accessing legal work, criminal capital is a function of embeddedness in offender networks that supply both the training and perhaps the opportunities to increase the returns from illegal "work."

Our results also imply that the reward incentives from crime and the criminal capital investments one makes may actually be an important mechanism in the processes of desistance from and persistence in crime. Moreover, we speculate that the concept of an illegal reservation wage may be a useful in bridging criminal returns and contemporary life course theories of desistance, which are grounded in the concept of human agency and posit that humans plan and

make choices that construct their life course (Elder 1994; Laub and Sampson 2003). For instance, Sampson and Laub's (1993) age-graded theory of informal social control argues that turning points such as marriage and employment strengthen conventional bonds and aids in the desistance process. It is likely that stronger bonds positively correlate with increased opportunity costs and one's reservation wage for illegal participation, along with other factors such as age and higher risk aversion (see also Lochner 2004). As our results reveal an ostensible threshold level for the returns to criminal experience to become apparent, it is possible that certain low experience offenders might actually find that, with a higher reservation wage, illegal income generation is no longer a desirable endeavor, even though their expected rewards have not diminished. Conversely, offenders who, through agentic action, have built criminal social capital and have made investments in training and specialization—might find that, even though their reservation wage has also increased through the same developmental progressions, the returns from offending are actually high enough to offset this. For example, Steffensmeier and Ulmer (2005: 55) note that a group of “high criminal capital offenders” do exist. Hence, this small group of highly capital-invested offenders will continue to persist in offending. This underscores the importance of differentiating high criminal capital offenders from chronic offenders who persist in offending for vastly different reasons. Again, we can draw analogy to the legal labor market, where for example an individual may be dissatisfied with a certain profession, but the investments she has made in training, education and job experience make the wage offer too attractive to change professions.

Furthermore, a much larger proportion of our offending sample participates and continues to participate in legal employment, for substantially lower wages. This reflects the centrality of the reservation wage in the problem context. We show that there are important determinates,

such as having a legal job, risk perception, and drug dependency, which strongly predict which individuals will select into illegal income-generating activities. This can provide important considerations for policy, and subsequent re-entry programs that seek to place returning offenders into meaningful and gainful employment.

Accordingly, we envision multiple avenues for continued study of the illegal wage equation and returns to criminal participation and criminal capital. For instance, it is possible that crime type indicators would yield important main effects (e.g., a wage premium for drug dealing) and possibly even interact with experience, which data limitations prevented us from exploring. Interestingly, although there is no important wage rate difference between those who report drug selling versus those who do not, there is an enormous difference for those who report selling other drugs besides marijuana (~\$719/week). Related to this, although our analysis is restricted to income-generating criminal experience, it is quite possible that instrumental violence is a key explanatory factor in higher earnings. Second, our results show that having a legal job is an important factor in not participating in illegal wage generating activities. While on average this likely is true, there still is the possibility that for some specific crimes, legal and illegal employment may in fact be *compliments* instead of substitutes. For instance, Reuter et al. (1990) speculate that drug dealers may retain legal employment as an opportunity to foster a potential client base, as well as a temporary respite from the risks of arrest and punishment that attend to illegal work. In general, there is a small line of research which acknowledges that certain individuals are not fully committed to either the legal or illegal markets, but rather drift between both depending on available wage opportunities (Fagan and Freeman, 1999; Grogger 1998; Myers 1983; Uggen and Thompson 2003). Therefore, we suspect that participation decisions in

either types of market as a function of wage offers in the other is a question worthy of investigation.

In addition to our measures, it is possible that there are other sources whereby one can gain criminal capital. One source is through familial ties. For example, Hagan (1993) discusses how parental criminality can dampen conventional prospects and deepen criminal ones. Another source of criminal capital is through institutionalization, discussed by Bayer, Hjalmarsson, and Pozen (2009), which may facilitate greater criminal embeddedness. Future research might look into the role institutions play in criminal embeddedness and its impact on the returns to crime.

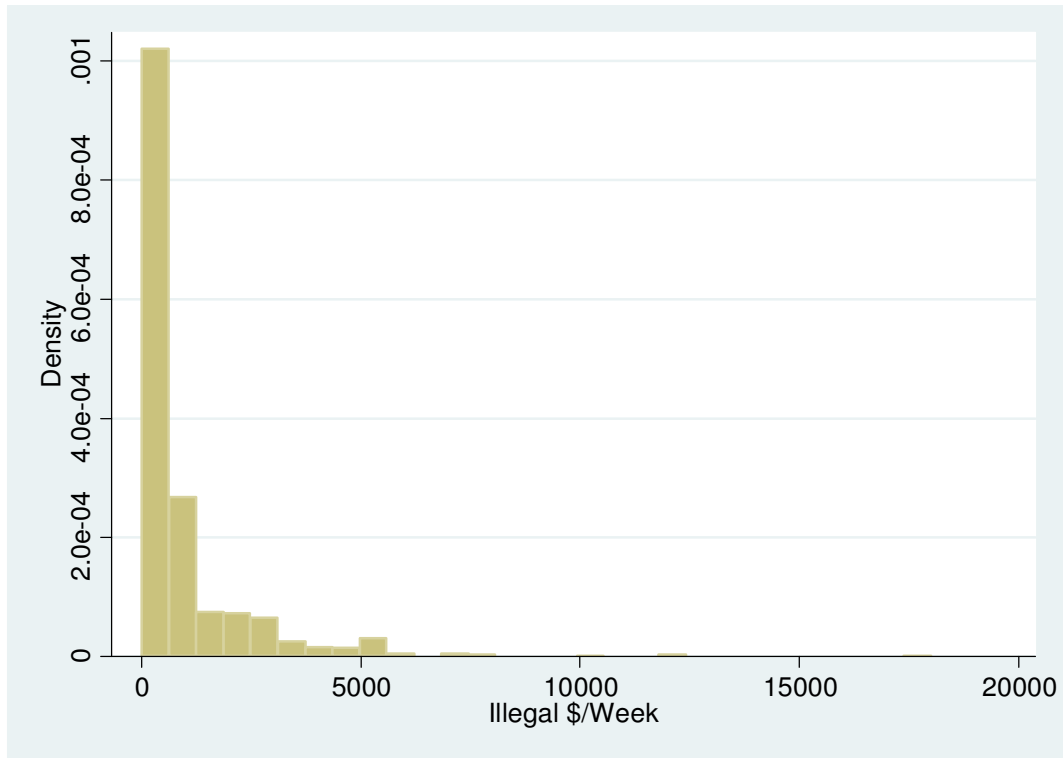
One possible limitation of our results is the failure to consider fixed unobserved heterogeneity in the main wage offer equation which may be correlated with criminal productivity characteristics (a main strength of Uggen and Thompson's findings). For instance, in labor market studies, economists often refer to unobserved 'ability' or 'motivation' as being an important determinant in the structural earnings equation. Indeed, some criminological scholars have speculated about the role of criminal ability (Morselli and Tremblay 2004; Steffensmeier and Ulmer 2005; Wright and Decker 1994), which if correlated with the both the wage offer and productivity indicators, could bias our results. We feel that the issue of criminal ability is worthy of its own theoretical framework and development as a potential key explanatory mechanism in the study of illegal markets. Accordingly, we advocate for this idea as an important topic for future scholarship.

The 'returns to criminal capital' is an area of criminological research that has been severely neglected, both theoretically and especially methodologically. A wage-based consideration of these issues, within a framework of human and social capital, opens up

additional areas of inquiry and furthers our understanding of how offenders make decisions whether to offend or whether to either temporarily or permanently avoid offending.

Figure 1. Histograms of Illegal Wage Rate

A) Reported Illegal Earnings per Week



B) Ln(Illegal Earning per Week)

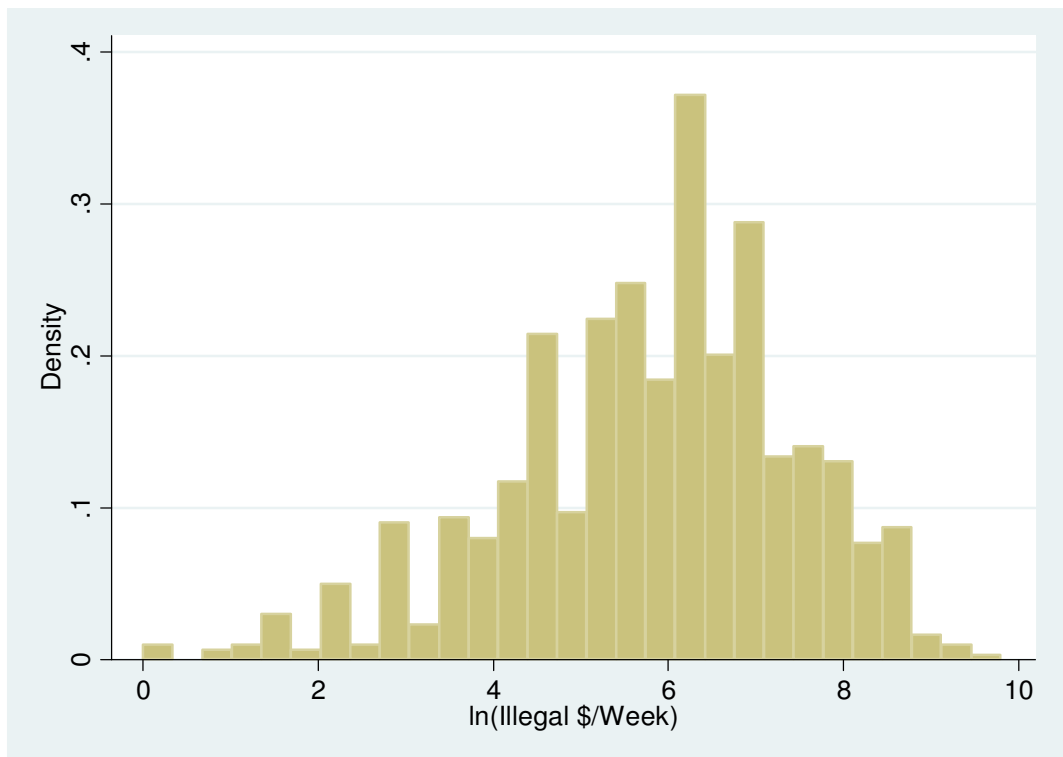


Figure 2. Mean Illegal Weekly Wage Rate by Experience Category

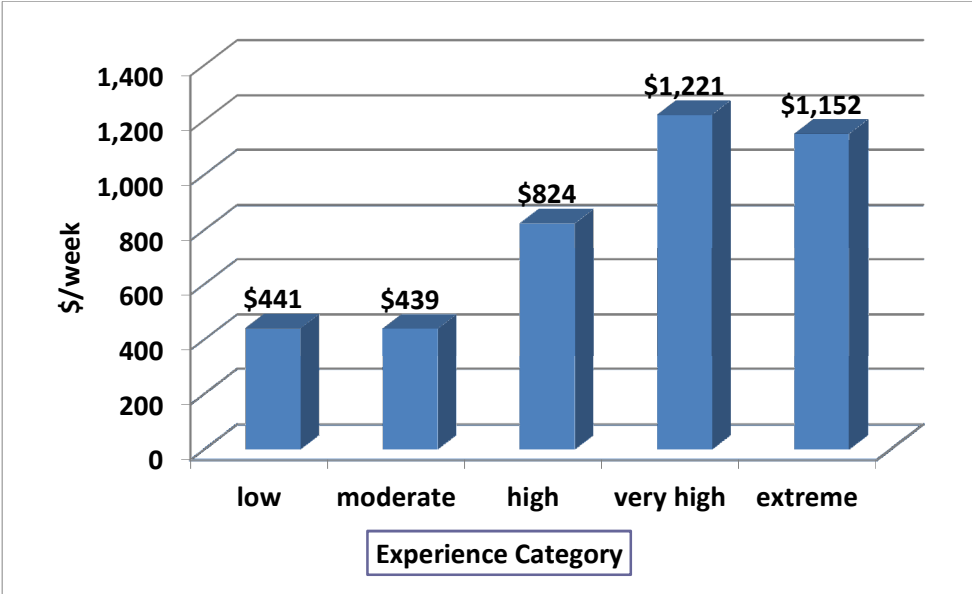


Table 1. Descriptive Statistics for Explanatory Variables

Panel A: Criminal Capital Indicators

	mean	s.d.	Med	Q1	Q3
specialize?	0.16	0.36	0	0	0
embeddedness	1.76	0.77	1.08	1.67	2.17
experience (total frequency):					
overall	41.9	102.2	0	0	16
illegal wage earners	162.3	177.6	20	110	213
non-earners	26.1	74.4	0	0	6

Panel B: Exclusion Restrictions

	total		illegal wage earners		non-earners	
	mean	s.d.	mean	s.d.	mean	s.d.
Age	18.28	1.40	18.31	1.35	18.28	1.40
legal job	0.39	0.46	0.34	0.47	0.40	0.49
exposure time	0.64	0.43	0.66	0.36	0.64	0.44
income risk perception	6.04	2.93	5.03	2.93	6.15	2.91
drug dependency	0.21	0.41	0.46	0.50	0.18	0.39

**Table 2. Descriptive Statistics for Illegal Wage Rate
(All Values is \$/Week)**

Overall:	
Mean	929
Median	422
Q1	102
Q3	1,000
st.dev.	1,491
Conditional on Experience:	
Low	441
Moderate	439
High	824
Very high	1,221
Extreme	1,152
Conditional on Specialization:	
Yes	1,034
No	834
Conditional on Embeddedness*:	
change per unit increase	149
change per standard deviation increase	127

***the value for embeddedness is a bivariate OLS coefficient**

Table 3. Parameter Estimates for Selection Equation, Binary and Censored Selection Equations

	probit estimates			tobit estimates		
	illegal participation (Y/N)			hours worked illegally		
	est. (s.e.)	<i>t</i>	<i>p</i> -value	est. (s.e.)	<i>t</i>	<i>p</i> -value
Moderate	0.441 (0.092)	4.80	0.000	7.098 (1.570)	4.52	0.000
High	1.113 (0.084)	13.27	0.000	17.336 (1.395)	12.43	0.000
Very high	1.379 (0.087)	15.88	0.000	21.949 (1.426)	15.39	0.000
Extreme	1.108 (0.089)	12.49	0.000	19.166 (1.469)	13.04	0.000
Specialize?	0.658 (0.063)	10.41	0.000	9.471 (0.960)	9.86	0.000
Embeddedness	0.143 (0.030)	4.82	0.000	2.512 (0.474)	5.30	0.000
Proportion Street Time	0.297 (0.071)	4.18	0.000	6.641 (1.205)	5.51	0.000
Income Crime Risk Perception	-0.042 (0.008)	5.05	0.000	-0.785 (0.130)	6.02	0.000
Age	-0.028 (0.021)	1.38	0.168	-0.054 (0.330)	0.16	0.871
Legal Employment?	-0.253 (0.062)	4.10	0.000	-5.098 (0.970)	5.25	0.000
Drug Dependency	0.719 (0.060)	11.98	0.000	11.397 (0.886)	12.86	0.000
Intercept	-1.834 (0.377)	4.87	0.000	-38.107 (6.302)	6.05	0.000
<i>N</i>	7,399			7,399		

Table 4. Estimates of Returns to Capital Indicators

	I		II			III		
	OLS		Heckman			Type III Tobit		
	est.	<i>p</i> -	est.	<i>p</i> -	change	est.	<i>p</i> -	change
	(s.e.)	value	(s.e.)	value	from OLS	(s.e.)	value	from OLS
moderate	0.069 (0.289)	0.406	-0.166 (0.313)	0.298	-139.7%	-0.244 (0.297)	0.206	-253.0%
high	0.740 (0.259)	0.003	0.181 (0.359)	0.307	-75.6%	0.130 (0.290)	0.328	-82.5%
very high	1.444 (0.247)	0.000	0.774 (0.387)	0.023	-46.4%	0.753 (0.293)	0.006	-47.9%
extreme	1.427 (0.247)	0.000	0.856 (0.347)	0.007	-40.0%	0.880 (0.270)	0.001	-38.3%
Specialize?	0.474 (0.120)	0.000	0.276 (0.141)	0.025	-41.8%	0.233 (0.126)	0.032	-50.8%
embeddedness	0.155 (0.064)	0.008	0.081 (0.065)	0.106	-47.8%	0.076 (0.063)	0.116	-51.0%
$\hat{\eta}$	-		-			-0.026 (0.006)	0.000	
intercept	4.323 (0.249)	0.000	5.712 (0.623)	0.000		5.672 (0.367)	0.000	
ρ	-		-0.343 (0.134)	0.019		-		
$\rho\sigma$	-		-0.537 (0.231)	0.019		-		
$\beta_{\text{mod}} = \beta_{\text{high}}$ (<i>F</i> -stat)	10.88	0.001	2.20	0.138		3.45	0.064	
$\beta_{\text{high}} = \beta_{\text{very high}}$	19.59	0.000	12.99	0.000		15.61	0.000	
$\beta_{\text{very high}} = \beta_{\text{extr}}$	0.01	0.905	0.27	0.600		0.73	0.394	
	<i>N</i> =833		<i>N</i> =833			<i>N</i> =833		

Notes: Standard errors are cluster corrected for individuals. *P*-values are reported for one-tailed test. Base category is low experience.

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ENDNOTES

¹ See for example: Mincer (1974), Willis (1986), Ashenfelter and Krueger (1994), Carneiro, Heckman and Vytlačil (2011).

² We use the term criminal capital to mean the criminal form of human capital.

³ Diminishing marginal returns to crime have been previously suggested by Grogger (1998).

⁴ In other words, one must be willing to make what she considers to be a rational decision to forego wages in the current period to instead acquire an additional year of schooling or enter job training that are linked to prospect of higher future earnings or faster wage growth. We credit a helpful reviewer for urging us to develop this particular point.

⁵ We offer several cautions on this complicated point. First, though we know of no formal criminological theories which suggest that individuals are attempting to maximize illegal earnings over their criminal career, and rational choice theories in criminology are generally silent on the role of time preferences (Nagin and Pogarsky 2001), it is plausible that some rational offenders could consider the opportunity for future illegal wages, even weighting the prospect against current period costs such as imprisonment. Second, there is a dearth of empirical research which directly comments on the relationship between legal and illegal work, and almost no formal theoretical predictions (except see Grogger 1998).

⁶ According to Burt (1998) and Coleman (1990), human capital is necessary to succeed, but is useless without the social relations to gain the opportunities to employ it. In Woolcock's (1998: 154) discussion of embeddedness and economic development in immigrant communities, he echoes this by stating: "The latest equipment and most innovative ideas in the hands or mind of the brightest, fittest person, however, will amount to little unless that person also has access to others to inform, correct, assist with, and disseminate their work". This is particularly true for returns to criminal capital.

⁷ Information regarding the rationale and overall design of the study can be found in Mulvey et al. (2004), while details regarding recruitment, a description of the full sample, and the study methodology are discussed in Schubert et al. (2004).

⁸ We alert the reader to some conceptual challenges inherent to measuring illegal wage rate. As a reviewer pointed out: "It is not clear...that there is a really sensible way to convert illegal earnings to a standard metric equivalent to an hourly wage that would be used for legal employment." We agree that such a standard metric for illegal earnings is a highly complicated yet fundamental measurement issue which the literature on criminal earnings has not yet adequately addressed. In prior studies of illegal earnings, the time frame over which illegal earnings were aggregated was quite large, leaving open the possibility for periods of inactivity to be unnecessarily included in the calculation, during which the offender was either not participating in illegal income-generating activities, or lacked opportunity due to incarceration or other incapacitation. In other words, aggregating illegal wages over too long of a period could potentially lead to inappropriate productivity comparisons among different offenders who might be spending vastly different amounts of time during the observation period involved in illegal activities. Of course, most studies of legal earnings do not face such an issue since wages are often calculated on a constant hourly basis, meaning differences among individual in hours worked is irrelevant. Yet it seems to us that "hours worked illegally" is almost impossible to accurately measure when comparing different acts which may vary in time even within individual, and the lack of any formal 'work' time records of illegal participation. Therefore, we settled on defining earning over weeks, as we feel it is the finest level of aggregation that is possible which still allows for some reasonable validity of self-reported activity, yet based on the life event calendar, we can still eliminate periods of inactivity due to incapacitation from the denominator. Of course, our weekly wage rate is by no means a perfect measure like some sort of 'illegal hourly rate' would be, yet we still feel it provides the most reasonable measure of comparison among different offenders, and we note that using a longer time period over which to aggregate earnings would only exacerbate measurement error.

⁹ The 10 self-report items include: 1) entered or broken into a building to steal something, 2) stolen something from a store, 3) bought, received, or sold something that you knew was stolen, 4) used checks or credit cards illegally, 5) stolen a car or motorcycle to keep or sell, 6) sold marijuana, 7) sold other illegal drugs (cocaine, crack, heroine), 8) prostitution, 9) taken something from another by force, using a weapon 10) taken something from another by force, without a weapon.

¹⁰ Murphy and Welch (1990) explicitly advocate the need for a flexible functional form specification for modeling returns to experience in the Mincer equation.

¹¹ We considered an imputation strategy where the mean of each individual's observed frequencies for each time period was used in place of the missing period to generate a cumulative sum. Using this method produced nearly identical results. There were also small amounts of missing data on the cases we did use on three predictors: peers, risk perception, and legal job (~5%, 3% and 1%, respectively). We retained all of these cases and used mean substitution conditional on participation to account for the missingness.

¹² Sensing there may be some reservation concerning the definition of specialization as two or fewer instead of one or fewer, we estimated all models using an indicator for endorsing one crime type. The results were very similar in terms of both sign and statistical significance.

¹³ Haynie and Osgood (2005) have noted one limitation of self-reported peer delinquency measures is that, since individuals tend to project their own behavior onto their friends, these measures may overestimate the true influence of peers. We feel this is less of an issue in our analysis, since our usage of this measure is intended to be an indicator of opportunity structure rather than peer influence, and more importantly, we are attempting to explain illegal wages, not offending, in a model which includes offending behavior as a separate regressor.

¹⁴ Note that this is not a problem of censoring, where we could simply treat the unobserved wage rate as zero and use a censored regression model (e.g., tobit).

¹⁵ To be clear, if H_0 were true, this would mean that the unobservable reasons why someone does not participate in an illegal market are not correlated with the unobservable determinants of their illegal wage offer. This does not seem reasonable if, for instance, individuals who have unobservable motivation to offend, in turn, earn higher wages because of their motivation and willingness, then ε_i and v_i are correlated.

¹⁶ The inverse Mills ratio is the ratio of the standard normal density function, sometimes written as $\phi(\cdot)$, evaluated at δz_i , to the standard normal cumulative distribution function, $\Phi(\cdot)$, or $\lambda(\delta z_i) = \phi(\delta z_i)/\Phi(\delta z_i)$.

¹⁷ The Heckman model can also be fit using a 'two-step' estimator, although assuming one has good exclusion restrictions, the ML procedure is more efficient.

¹⁸ Some might point out that this specification still depends on a normality assumption. In fact, others have proposed semi-parametric estimators to circumvent this issue (e.g., Honore, Kyriazidou and Udry 1997). However, due to the very high proportion of truncation in our sample, these estimators are unfortunately not applicable in our case.

¹⁹ For instance, in the female labor force participation example, in sample of married women Mroz (1987) uses non-wife income (i.e., husband wages), as one exclusion restriction. The logic here is if the husband is a high earner, it should make the wife less willing to enter the labor force herself, but once she does, her husband's earnings would have no bearing on her own wage offer.

²⁰ Bushway et al. (2007:163-165) provide an excellent description of all of the potential problems of estimating a Heckman model without a proper exclusion restriction.

²¹ These results are comparable to past findings on illegal earnings. Freeman (1996) found that among a group of Boston youth who make money from crime, occasional offenders and weekly offenders earned \$250 and \$448 respectively. Viscusi (1986) surveyed inner-city youth (15-24 years) from Boston, Chicago and Philadelphia and found that the average monthly illegal income was \$272. Among a sample of homeless youth in Toronto and Vancouver, McCarthy and Hagan (2001) found that the average daily earnings of participants in the drug trade was \$101.

²² Some may wonder if the rate premium for increased experience might merely reflect a volume effect based on higher participation. This is explicitly why we consider rate as the outcome, to reduce this possibility. The denominator (weeks worked) is generally increasing with experience. For instance, on average those individuals with extreme experience report 21%, 56% and 82% more total illegal hours than the very high, high and moderate experience groups, respectively.

²³ Ideally, we would like to know how the wage rate varies with certain illegal activities. However, two things prevent us from doing this. First, there is a high degree of overlap in the sample with individuals endorsing multiple crime types, including 80% who report drug selling activity. Second, we are unable to disaggregate the illegal income earned by crime types, meaning we cannot match earnings to specific crimes. We note, however, that there is no important difference in mean rate for those who report selling drugs versus those who do not. We return to this idea in the discussion section.

²⁴ On this point, a reviewer challenged us to more deeply consider three of our exclusion restrictions. First, with respect to risk perceptions, s/he noted "offenders with lower risk perceptions might take more risky chances, and thus have a tendency to make bigger scores." Second, s/he wondered if drug dependency might make "offenders 'sloppy' ... [t]his means that drug dependent offenders would earn less illegally, net of their criminal experience." In both of these instances, the reviewer argued that although s/he felt confident that these two variables did predict

selection, they in fact also might belong in the main wage equation. We then tested additional model specifications including both variables, separately and jointly, and found no significant effects of either variable on income, nor did the coefficients on our capital predictors materially change with inclusion. Finally, due to concerns over age being correlated with multiple things, we fit the model without age as an exclusion so as not to rely on it. Again, our results were robust. We note that these specification checks actually enhance our confidence in the validity of our results, as they show that our findings are not sensitive to any one assumption. Detailed results are available upon request.

²⁵ In a log-linear model with dummy predictors, the percentage impact of a change in the predictor from 0 to 1 on the (untransformed) outcome Y is $100 * [100 * [e^{\beta} - 1]]$.