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The Returns to Criminal Capital

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Abstract

Human capital theory posits that individuals 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, the focus of some speculation and limited empirical study, remains considerably less developed theoretically and methodologically. This article 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, important illegal wage premiums are associated with investments in criminal capital, notably an increasing but declining marginal return to experience and a premium for specialization. Furthermore, as in studies of legal labor markets, we find strong evidence that, if left unaccounted for, nonrandom sample selection causes severe bias in models of illegal wages. We discuss theoretical and practical implications of these results, along with directions for future research.

Keywords

criminal capital, illegal earnings, social capital, sample selection

A half a century ago, Becker (1962:9) noted the importance of "activities that influence future real income through embedded resources in people," or what is typically called *human capital*. The notion that individuals generate positive outcomes, such as higher earnings, through investment in activities, such as education and training, has made the study of human capital a long-standing and widespread source of inquiry in economics, sociology, and education. Empirical economics, for instance, has extensively studied the return to personal investments in education. Beyond their theoretical importance, these studies frequently generate popular interest and contentious debates.[1]

Criminological discourse has also considered the theory of human capital. Unlike its conventional counterpart, however, 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,

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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., Matsueda et al. 1992; McCarthy and Hagan 2001; Morselli, Tremblay, and McCarthy 2006; Nguyen and Bouchard 2013; 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 has not been examined in the same detail as conventional human capital, making it premature to make connections between the two. Furthermore, studies that explore variation in criminal earnings have found a substantial positive association between indicators of criminal capital and aggregate criminal earnings (McCarthy and Hagan 2001; Uggen and Thompson 2003). However, these studies have not adequately accounted for key methodological obstacles that often arise in the study of labor markets, resulting in potentially inconsistent estimates that substantially reduce generalizability.

Examining 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 (see Cornish and Clarke 1986; Paternoster and Simpson 1993; Piliavin et al. 1986; Piquero et al. 2011). This suggests that individuals are highly responsive to rewards from crime. Stated differently, illegal rewards may have a positive impact on offending frequency and overall criminal career length. 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).

The importance of understanding criminal capital, coupled with its relatively few empirical studies, animates the present study. Guided by classic human capital theory, this article attempts to develop a more robust theory of criminal capital by considering the nature of illegal earnings and how certain criminal productivity indicators may yield higher returns in the illegal labor market. We then test these indicators using 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 showing that, similar to studies of the legal labor supply, studies of illegal earnings suffer from important sample selection issues that 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. Investment in human capital includes a variety of activities, such as health and nutrition (Schultz 1981), but the most salient forms of investment are through education, including investments in formal schooling (Mincer 1974), informal education (Schultz 1981), and general and specific on-the-job training that increases workers' skills (Becker 1962). Human capital has a rich history of theoretical and empirical development and an impressive amount of scholarship devoted to its study (see Altonji, Blom, and Meghir 2012).

Mincer (1958), Schultz (1960, 1961), and Becker (1962) have each made seminal contributions to human capital theory, in particular,

the idea that investment in human capital is an inseparable part of an individual, which positively affects earnings. In his influential piece, "Investment in Human Capital," Schultz (1961) argued that estimating the magnitude of human investment is not a straightforward task because qualities such as skills and knowledge are considered both consumption and investment, thereby posing conceptual difficulties and identification challenges. For example, obtaining a formal education has opportunity costs because individuals must forgo earnings while at school or when participating in on-the-job training. Given these factors, Schultz (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, that 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." Mincer highlighted that the relationship between experience and wages does not rise linearly—rather, it follows an age-earnings profile in which experience increases wage rates at a marginally decreasing rate. Hundreds of empirical studies have found support for the Mincer earnings function, 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 two types of job 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 a particular firm. Investment in general training provides less of a rate of return but is a transportable stock of knowledge and skills.

In summary, several fundamental features of human capital theory should be considered before researchers can 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 versus specific training. Investment in both general and specific training should increase earnings; however, specific training will have greater returns for a particular job.

Does Criminal Capital Exist?

Does a criminal analog to human capital exist? McCarthy and Hagan (1995) first coined the term *criminal capital,* mirroring 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 increase the frequency of drug selling and theft. Although they do not directly consider monetary returns, they set the conceptual groundwork for the idea that investment in criminal training can be beneficial.

Other studies allude to the concept of criminal capital and its potential parallels with human capital, suggesting that 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." Ethnographic studies illustrate that training and time go into the development of skills in thievery (Steffensmeier and Ulmer 2005; Sutherland 1937), hustling and fencing (Klockars 1974), drug dealing (Fagan 1992; Williams 1989), 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 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; Logie, Wright, and Decker 1992; Nee and Meenaghan 2006; Wright and Logie 1988). Although a number of criminologists have highlighted the value of specialized skills (e.g., Cloward and Ohlin 1960; Decker, Wright, and Logie 1993; Shaw 1930; Shover 1996; Sutherland 1937; Topalli 2005), 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 to crime. This work consistently shows that measures such as criminal experience, specialization, and tutelage are positive and significant predictors of greater aggregate illegal earnings (e.g., Morselli et al. 2006; Nguyen and Bouchard 2013; 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 an offender was arrested in the 36-month study period. They also included a quadratic arrest term, because, guided by human capital theory, they expected to find diminishing returns to criminal experience. Uggen and Thompson (2003) found a significant curvilinear relationship between their proxy for criminal experience and total monthly illegal earnings.

Offenders can accumulate criminal capital through several mechanisms. Sutherland's (1937, 1947) work is perhaps the most notable, with his discussion of differential association and his interviews with a professional thief. For Sutherland (1947:6), learning criminal behavior is no different from learning any behavior: through intimate personal groups, "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." Through his interviews with a professional thief, Sutherland (1937) illustrated a process very similar to the acquisition of human capital. He described a selection process through informal social networks, indoctrination into the culture of thieves, and tutelage of requisite skills and techniques. Akers (1973) extended the notion of differential association in his social learning theory to argue that people acquire and maintain behavior through imitation or modeling others' behavior, definitions, which are expressions of values and norms, and differential reinforcement contingencies (rewards and punishments). 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 (for a discussion of various mechanisms of peer influence, see Cloward and Ohlin 1960; Osgood et al. 1996; Stafford and Warr 1993; Warr 2002). Finally, Bayer, Hjalmarsson, and Pozen (2009) explicitly hypothesized that individuals can build criminal capital while in correctional facilities through exposure to peers.

Differences between Criminal Capital and Human Capital

Human capital theory provides a useful theoretical point of departure for exploring the concept of criminal capital, but a closer comparison

reveals a number of ways these concepts diverge. First, human capital and criminal capital are both grounded in a rational choice framework (Becker 1968), but the former is necessarily steeped in the concept of a future-oriented agent.[4] In addition to its yield, another way to measure human capital at the individual level is through a cost-based approach that considers both investment costs and discounted future income (Jorgenson and Fraumeni 1989; Kendric 1976). This method represents the familiar notion of delayed gratification on the part of the individual investing in human capital. In the extensive literature on the 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, strong theoretical and empirical evidence suggests 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 contrast to economic theories that assert current 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). More specifically, illegal market entry decisions are more likely to be driven by the immediacy of criminal gains, 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.

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 models of illegal labor supply and criminal capital, while sharing some similarities to human capital and wages, could be quite different from legal supply models—specifically, illegal entry decisions are perhaps a function of *both* immediate illegal and discounted (or forgone) legal incentives. Indeed, some descriptive evidence suggests that legal and illegal work are not always seen as trade-offs (Fagan 1992; Freeman 1996; Reuter, MacCoun, and Murphy 1990; Viscusi 1986).[5] To measure criminal capital, one must thus use an income-based approach, rather than cost-based, which measures human capital through productivity measures, that is, its rate of return (Mincer 1974; Schultz 1961).

A second, more fundamental distinction between human 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 classic human capital theory. Coleman (1988:S101) argued that the traditional depiction of human capital was undersocialized, and he suggested that social structure could be incorporated into economists' principle of rationality: just as "human capital can facilitate productive activity, social capital does as well." For example, groups whose members trust each other are able to accomplish more than groups with lower 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. Most economic actions occur within social networks (see also McCarthy 2002).

Social capital exists in several different forms. It can be a collective resource that facilitates mutual trust and informal social control (e.g., Sampson, Morenoff, and Earls 1999; Skogan 1990) or produces civic engagement (Putnam 2000). Alternatively, 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 compelling demonstration of the importance of social capital is in migrant communities. Several scholars underscore the importance of social capital in migration efforts (Garip 2008; Massey and Aysa-Lastra 2011) and in prosperous immigrant and ethnic entrepreneurship communities (Aguilera 2005; Zhou and Logan 1989). Through community networks, members of immigrant communities have access to information, start-up financial capital, and a dedicated labor supply (Portes and Sensenbrenner 1993). Similarly, social capital can contribute to prosperity and cohesion among criminal networks (Browning, Dietz, and Feinberg 2004; Portes 1998). In terms of criminal capital, social capital facilitates both accumulation and greater returns.[6]

One can accumulate human capital through social capital; criminal capital, however, is arguably *more* reliant on criminal social capital because of the informal social nature of most criminal enterprises. 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 through 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: the informal economy is dependent on social ties, trust, and mutual obligations for effective functioning (see also Portes and Haller 2005). Therefore, embeddedness, or ongoing social relations in criminal social networks, likely plays a crucial role in both investment in and returns to criminal capital. Indeed, prior studies show that criminal embeddedness positively contributes to greater illegal earnings (e.g., Levitt and Venkatesh 2000; McCarthy and Hagan 2001; Morselli et al. 2006).

These studies underscore important differences between human and criminal capital. Traditional human capital theory inherently and necessarily draws attention to individuals and their positions relative to social and economic institutions, but this strictly individualistic view of human capital only partially translates to the complex intersection of social, structural, and individual factors that affect the tangible returns to criminal capital. We elaborate these concerns in our theoretical specification in the following sections.

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 general and specific experience, using a sample of serious adolescent offenders for whom we have detailed information about illegal wages and participation activity. Second, unlike previous studies that consider total wage volume, we model the outcome of wage *rates* to capture criminal productivity returns. We hypothesize that participants' wage rates will increase as their criminal capital indicators rise; 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 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. Although this estimator is sometimes criticized for over-sensitivity to distributional and functional form assumptions, as well as general misuse in criminological research (Bushway, Johnson, and Slocum 2007), the strength of our results rests on our use of multiple exclusion restrictions (i.e., variables that are important to explain selection, but given productivity characteristics, do not explain illegal wage rates) that mitigate these concerns. Furthermore, we exploit the fact that our data reveal 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 our reliance on the nonlinearity assumptions in the standard model.

DATA

We analyze data from the Pathways to Desistance study (Mulvey 2012), 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), Arizona or Philadelphia County, Pennsylvania. A total of 1,354 adolescents were enrolled in the study, representing approximately one in three adolescents adjudicated on charges in each locale during the recruitment period (November 2000 through January 2003). The study sample contains mainly non-white (44 percent African American, 29 percent Hispanic) males (86 percent) who were, on average, 14.9 years old at the time 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 percent retention). As described below, not every individual reported involvement in illegal income-generating activity in all periods (this is the selection problem). In each period, for each individual, we have the number and types of income-generating crimes they reported committing, if any, along with their age, income risk perceptions, and drug dependency. Additionally, we used a life-event calendar to record detailed information regarding the number of weeks in which participants were engaged in legal and illegal activities and the total amount of money earned from each activity each month. The life-event calendar also allowed us to determine the proportion of time each individual was not locked up in a secure facility (exposure time). Research shows life-event calendars are reliable tools in studies of criminal offending (Morris and Slocum 2010).[7]

Outcome Variable

Illegal wage rate. We calculated the illegal wage rate by dividing an individual's total reported illegal earnings in a month by the total number of weeks worked across all illegal jobs. We calculated the number of weeks by multiplying each week a participant worked by 1.3 to account for the fact that all months are not exactly four weeks long (52 weeks in a year divided by 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 respondents out of the 1,354 total sample reported earning illegal wages in at least one period (around 37 percent). Of these 496, more than half reported earning only illegal wages in one period ($n = 265$). Pooling all 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, to deal with skew we take the natural log of the illegal wage rate as the dependent variable. Figure 1 displays histograms of the untransformed and transformed rates. We explore a descriptive summary of this outcome in more detail below.

Criminal Capital Measures

Criminal experience. We measure criminal experience as an individual's cumulative frequency of participation in 10 illegal income-generating activities, derived from a common self-reported offending (SRO) measure recorded in each period (Huizinga, Esbensen, and Weiher 1991; see Thornberry and Krohn [2000] for a summary of the usefulness and validity of self-reported delinquency measures in criminological research). In each

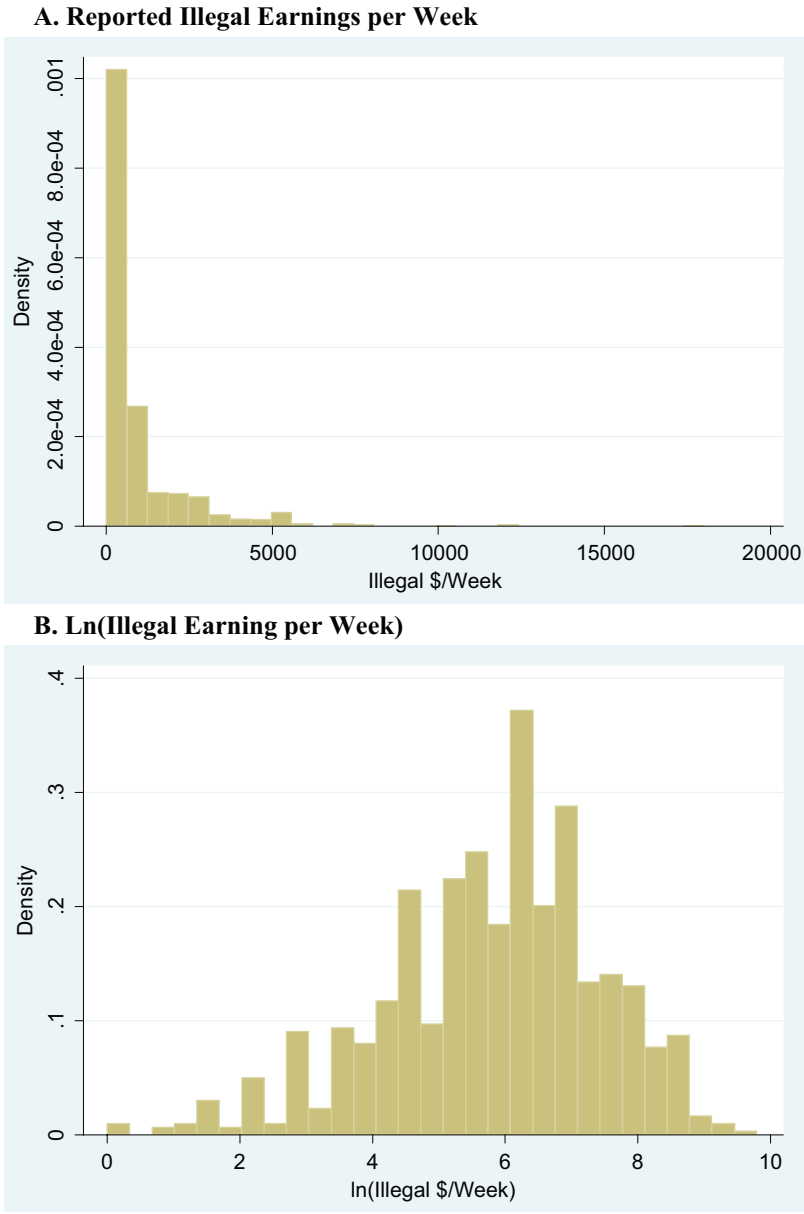

Figure 1. Histograms of the Illegal Wage Rate

period, individuals were asked whether they had committed each of these 10 crimes in the past six months, and if so, how many times.[9] We summed these values to arrive at a total period frequency and then cumulative frequency, providing a cumulative measure of general experience with income-generating crimes.[10]

Because cumulative income offending frequency is skewed, we created a vector of categorical experience variables using the quartiles of the conditional distribution of cumulative frequency based on participation. We then subdivided the lowest category in two to better capture variation among nonparticipants. This yielded five unique experience

categories: low (0 to 2 cumulative crimes reported), moderate (3 to 20 crimes), high (21 to 110 crimes), very high (111 to 213 crimes), and extreme (more than 213 crimes). Besides dealing with the skew problem, this strategy allows us flexibility in detecting potential nonlinear marginal returns to criminal experience (Murphy and Welch 1990).

Of the original $N = 883$ observations, 88 cases (9.9 percent) 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. We were thus unable to calculate a total cumulative frequency score. Of these 88 cases, we could safely conclude that 38 fell into the extreme category based on observed experience that 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. We therefore excluded 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 reported engaging in two or fewer unique crime *types* during the observation period and 0 if otherwise. We define specialization as two or fewer instead of one or fewer because certain pairs of crimes are natural complements (e.g., stealing and selling stolen goods). Among individuals reporting illegal wages, 56.7 percent were specialized. Importantly, there was variability in specialization among nonmarket participants (or else it would be a perfect predictor of participation). This is plausible because 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. We computed an individual's score as the mean rating of the prevalence of friends who engaged in 12 types of delinquent behavior (e.g., "How many of your friends have sold drugs?"). The subscales had very high internal consistency ($\alpha = .93$).[12]

Panel A of Table 1 reports descriptive statistics for the two criminal capital/productivity measures as well as embeddedness. Notice that when comparing illegal wage earners to nonearners, the distribution of experience is very different, and each indicator has important mean differences (all p-values < .001).

MODEL

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

$$\ln(iw_i) = \beta_0 + \beta_1 exp_i + \beta_2 spec_i + \beta_3 embed_i + \varepsilon_i \quad (1)$$

where $\ln(iw_i)$ is the natural log of the rate of reported weekly illegal earnings; *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 capital 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 requires an alternative estimation strategy to produce consistent estimates.

Table 1. Descriptive Statistics for Explanatory Variables

Panel A. Criminal Capital Indicators	Mean	s.d.	Med.	Q1	Q3
Specialize?	.16	.36	0	0	0
Embeddedness	1.76	.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
Nonearners	26.1	74.4	0	0	6

	Total		Illegal Wage Earners		Nonearners	
Panel B. Exclusion Restrictions	Mean	s.d.	Mean	s.d.	Mean	s.d.
Age	18.28	1.40	18.31	1.35	18.28	1.40
Legal job	.39	.46	.34	.47	.40	.49
Exposure time	.64	.43	.66	.36	.64	.44
Income risk perception	6.04	2.93	5.03	2.93	6.15	2.91
Drug dependency	.21	.41	.46	.50	.18	.39

The Problem of Sample Selectivity in Modeling Illegal Wages

Illegal wage data suffer from incidental truncation, or sample selection that occurs because we observe the illegal wage offer only for individuals who participate in illegal markets; otherwise, their wage offer is unobservable (not zero). Furthermore, it is very likely that the selection mechanism is endogenous. OLS in this case would yield biased estimates of the true model parameters, that is, those 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 suggests that an individual will choose to participate in the labor market only 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 one is to enter the market *ceteris paribus*. This issue often arises 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. Estimates of returns to productivity characteristics for such a subsample thus lead to biased estimates for the entire population. Various scholars have discussed the identification issue in the context of sample selection (see Berk 1983; Bushway et al. 2007).

To our knowledge, only one study on illegal earnings addresses issues of sample selection. McCarthy and Hagan (2001) explore whether specialization in drug selling is associated with greater returns. They first used a probit model to estimate the probability of participating in drug selling in the first wave, and then employed a tobit model to assess drug selling income in the second wave. However, this strategy essentially treats the zeros as being censored at zero—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 that would have occurred had the problem been ignored altogether. In summary, sample selection issues likely plague studies of illegal wages, which, if ignored, will lead to biased estimates. Unfortunately, very few studies adequately consider this issue, making previous estimates on criminal capital indicators difficult to generalize.

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

Dealing with sample selection requires a second, selection equation:

$$s_i = 1 \cdot [\delta \mathbf{z_i} + \upsilon_i > 0] \quad (2)$$

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 otherwise; and $\mathbf{z_i}$ is a vector that includes all of the regressors in Equation 1, as well as variables that, by assumption, predict 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,* because 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 υ_i, are jointly normally distributed with correlation ρ. Under the null hypothesis H_0: ρ = 0, selection is exogenous and Equation 1 can be consistently estimated using OLS. Rejection of H_0 implies a selection problem, and we will need to correct for it. The parameters in Equation 1 can be consistently estimated by first estimating Equation 2 using probit, and then using these first-stage estimates to calculate the inverse Mills ratio, $\lambda(\mathbf{\delta z_i})$, for each individual.[13] This term can be included as an additional regressor in Equation 1, which yields the following conditional expectation:

$$E\left[\ln(iw_i) \mid s_i = 1, exp_i, spec_i, embed_i\right]$$
$$= \beta_0 + \beta_1 exp_i + \beta_2 spec_i + \beta_3 embed_i + \rho_{\varepsilon,v}\sigma_\varepsilon \lambda(\delta \mathbf{z_i}) \quad (3)$$

The model can be estimated using a full maximum likelihood procedure, which by accounting for the λ term will yield consistent estimates of the β parameters. This procedure will also provide estimates of the selection equation δ parameters from Equation 2 via probit. Notice that the coefficient on the λ term in Equation 3 is $\rho\sigma_\varepsilon$ (where σ_ε denotes the variance of ε), meaning that failure to reject it is equal to zero implies ρ = 0, which is the same test of H_0.

A Tobit Selection Equation

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

$$h_i = \max(0, \pi \mathbf{z_i} + \eta_i), \quad (4)$$

where h_i is the amount of illegal weeks supplied; $\ln(iw_i)$ is observed only when $h_i > 0$; the vector $\mathbf{z}$ again contains exclusion restrictions; and $\boldsymbol{\pi}$ is the parameter vector. We make very similar normality assumptions to the standard Heckman model, except now we assume the relationship between 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

$$E[\ln(iw_i) \mid h_i > 0, \eta_i, exp_i, spec_i, embed_i]$$
$$= \beta_0 + \beta_1 exp_i + \beta_2 spec_i + \beta_3 embed_i + \gamma\eta_i. \quad (5)$$

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 $H_{0.1}$: γ = 0 using the *t*-statistic from OLS implies there is a sample selection problem (Vella 1992).

Amemiya (1985) refers to this correction procedure as a *type III Tobit* (T3T) model. Wooldridge (2002) offers two key benefits of this model over the standard Heckman estimator. First, using more information in the selection equation will result in a more efficient estimate. Second, and more importantly, any frailty of a valid exclusion restriction is less of a problem here, as there will be variation in the tobit residuals just based on variation in weeks of participation.

Exclusion Restrictions

Recall that we impose multiple exclusion restrictions on Equation 1, that is, we assume that some variables appear in the selection equation but not in the wage equation, implying that, conditional on the capital/productivity characteristics, these regressors have no additional impact on the wage offer. Absent such assumptions, identification of the model is entirely due to strong functional form assumptions, the failure of which can be highly problematic (see Bushway et al. 2007). 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 six-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), and it is particularly relevant for nonparticipation (i.e., desistance) in the current sample of serious offending adolescents (Sweeten, Piquero, and Steinberg 2013). Yet, any observed wage premium for older offenders would likely be due to the correlation between age and experience, as opposed to age itself. A 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 individuals who did not participate.

Income risk perception. Research shows that an offender's subjective risk perception is generally negatively associated with offending decisions (Nagin 1998), particularly when considering income-generating crimes (Loughran et al. 2011). Specifically, offenders' reservation wage, and by extension their participation decisions, 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 was measured in each period by asking respondents how likely it is they would be caught and arrested for the following four income-generating crimes: robbery with gun, breaking into a store or home, stealing clothes from a store, and auto theft. Response options range from 0 (no chance) to 10 (absolutely certain to be caught). We took the average of the four risk perceptions as the total measure. The mean risk score for respondents who reported illegal earnings, 5.03, is lower, as expected, than the mean for those who did not, 6.15.

Legal employment. Employment in a legal job should be negatively related to illegal market participation, because research consistently shows that legitimate employment aids 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. There is thus no discernible reason to suspect that involvement in the legal market should influence one's returns in the illegal market. Our measure is an indicator generated from the life-event calendar equal to 1 if an individual reported having legitimate legal employment at any time during the observation period, and 0 otherwise. Among illegal market participants, 34.5 percent

reported legal employment, compared to 39.6 percent of nonparticipants.

Drug dependency. Uggen and Thompson (2003) found drug dependency was the most important indicator of illegal wage volume, suggesting participation in the illegal market is necessary to generate the types of funds needed for drug procurement. Moreover, additional motivation due to the prospect of substance use likely lowers one's reservation wage. Importantly, Uggen and Thompson's analysis considers *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 because these individuals probably have a lower reservation wage), then volume of participation could explain this result, rather than the notion that drug users' illegal wage rate should be higher. Subjects were asked to report on several indications of drug dependency in each recall period. Respondents who answered affirmative to one or more symptoms were considered drug dependent and coded 1. Subjects who did not report any symptoms of dependency were coded 0. Respondents who reported involvement in an illegal market reported considerably more drug dependency than did nonparticipants (45.6 versus 18.4 percent).

Exposure time. This measure is the proportion of time during the six-month recall period an 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 and colleagues (2001) demonstrated that individual offending patterns changed 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 this measure, we included only stays in settings without access to the community (e.g., jail or prison; see Mulvey, Schubert, and Chung 2007). Individuals who reported illegal market participation during a period had a slightly higher average exposure time than did nonparticipants (66.2 versus 64.0 percent).

The number of exclusion restrictions is a strength of our analysis, because it means 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, note that in all reported hypothesis tests throughout the remainder of the article, standard errors are cluster corrected at the individual level. This is important because we are using pooled data, so the error terms are likely not independent, and without such a correction, the standard errors are underestimated by as much as 30 percent.

RESULTS

Descriptive Statistics on Illegal Wage Rates

Table 2 reports descriptive statistics for the illegal wage rate. Overall, the mean reported illegal wage rate (conditional on reporting) is $929/week. This is about 320 percent higher than the mean reported *legal* wage rate in the sample of $290/week. 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 reflects a 78 percent premium for the illegal rate ($422/week versus $245/week). Finally, the illegal interquartile range extends from $102/week to $1,000/week, suggesting there is considerable variability beyond just the outliers.[14]

Table 2 also reports how the average wage rate varies with our criminal capital measures. First, the mean wage rate is generally *increasing* as a function of cumulative experience (as

Table 2. Descriptive Statistics for Illegal Wage Rate (All Values in $/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[a]	
Change per unit increase	149
Change per standard deviation increase	127

[a]The value for embeddedness is a bivariate OLS coefficient.

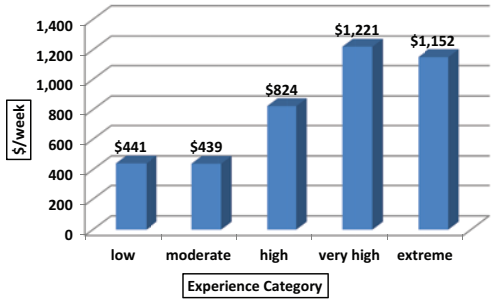

Figure 2. Mean Illegal Weekly Wage Rate by Experience Category

shown in Figure 2). Moreover, this relationship appears to be nonlinear. The mean reported illegal wage rate for the low experience group is $441/week, and the mean for the moderate group is almost identical, $439/week. However, there is a large premium going from the moderate to high experience group ($F = 8.28$; $p = .002$), for whom the rate is $824/week (a 91 percent increase). Similarly, there is another large increase in wage rate between the high and very high levels of experience ($F = 5.05$; $p = .025$), increasing to $1,221/week. This represents a 48 percent increase over the high rate, and a 178 percent increase over the moderate rate. Finally, there appears to be no premium for the extreme experience group; in fact, the mean wage rate actually *decreases* slightly, although we cannot reject a null of no difference between the extreme and very high rates ($F = .20$, $p = .655$). This set of results suggests 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.

We also find a 24 percent higher premium ($t = 1.99$, $p = .046$) for the mean rate of specialized ($1,034/week) versus nonspecialized ($834/week) individuals. Finally, criminal embeddedness is also strongly and positively related to illegal wage rate ($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.[15]

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 estimates from the first-stage selection equations for both the probit and tobit selection models (Equations 2 and 4, respectively). In both models, each excluded regressor has a statistically significant impact on selection, with the lone exception of age in the tobit model. Again, although we cannot explicitly test if our exclusion restrictions are valid, this set of results is highly congruent with our assumptions.[16]

In all cases, coefficient signs are consistent with theoretical predictions. Individuals with a higher proportion of street time and those engaged in drug use were more likely to

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.)	*t*	*p*-value	est. (s.e.)	*t*	*p*-value
Moderate	.441	4.80	.000	7.098	4.52	.000
	(.092)			(1.570)		
High	1.113	13.27	.000	17.336	12.43	.000
	(.084)			(1.395)		
Very High	1.379	15.88	.000	21.949	15.39	.000
	(.087)			(1.426)		
Extreme	1.108	12.49	.000	19.166	13.04	.000
	(.089)			(1.469)		
Specialize?	.658	10.41	.000	9.471	9.86	.000
	(.063)			(.960)		
Embeddedness	.143	4.82	.000	2.512	5.30	.000
	(.030)			(.474)		
Proportion Street Time	.297	4.18	.000	6.641	5.51	.000
	(.071)			(1.205)		
Income Crime Risk Perception	–.042	5.05	.000	–.785	6.02	.000
	(.008)			(.130)		
Age	–.028	1.38	.168	–.054	.16	.871
	(.021)			(.330)		
Legal Employment?	–.253	4.10	.000	–5.098	5.25	.000
	(.062)			(.970)		
Drug Dependency	.719	11.98	.000	11.397	12.86	.000
	(.060)			(.886)		
Intercept	–1.834	4.87	.000	–38.107	6.05	.000
	(.377)			(6.302)		
N	7,399			7,399		

select into illegal wage-generating activity and to 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 participated fewer hours or weeks.

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

Returns to Criminal Capital

Table 4 reports estimates of the parameters of the main wage equation (Equation 1) generated using pooled OLS, Heckman, and T3T estimation. The OLS results show that when considering all of the criminal capital indicators simultaneously, returns to each indicator are 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

Table 4. Estimates of Returns to Capital Indicators

	I		II			III		
	OLS		Heckman			Type III Tobit		
	est. (s.e.)	*p*-value	est. (s.e.)	*p*-value	Change from OLS	est. (s.e.)	*p*-value	Change from OLS
Moderate	.069 (.289)	.406	–.166 (.313)	.298	–139.7%	–.244 (.297)	.206	–253.0%
High	.740 (.259)	.003	.181 (.359)	.307	–75.6%	.130 (.290)	.328	–82.5%
Very High	1.444 (.247)	.000	.774 (.387)	.023	–46.4%	.753 (.293)	.006	–47.9%
Extreme	1.427 (.247)	.000	.856 (.347)	.007	–40.0%	.880 (.270)	.001	–38.3%
Specialize?	.474 (.120)	.000	.276 (.141)	.025	–41.8%	.233 (.126)	.032	–50.8%
Embeddedness	.155 (.064)	.008	.081 (.065)	.106	–47.8%	.076 (.063)	.116	–51.0%
$\tilde{\eta}$						–.026 (.006)	.000	
Intercept	4.323 (.249)	.000	5.712 (.623)	.000		5.672 (.367)	.000	
ρ			–.343 (.134)	.019				
$\rho\sigma$			–.537 (.231)	.019				
$\beta_{mod} = \beta_{high}$ (*F*-stat)	10.88	.001	2.20	.138		3.45	.064	
$\beta_{high} = \beta_{very\ high}$	19.59	.000	12.99	.000		15.61	.000	
$\beta_{very\ high} = \beta_{extr}$	.01	.905	.27	.600		.73	.394	

Note: $N = 833$. Standard errors are cluster corrected for individuals. *P*-values are reported for one-tailed tests. Base category is low experience.

results in a 110 percent increase in the expected illegal wage rate.[17] We find wage premiums for specialization (around 61 percent) and criminal embeddedness (a one-unit increase in embeddedness corresponds to a 15 percent increase in the wage rate).

Still, results from both of 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: $\rho = 0$ ($p = .019$). In the T3T model estimates, the *t*-ratio on the fitted residuals term is −4.43, meaning we can reject H_0: $\gamma = 0$ ($p < .001$). But the best indicator of selectivity bias is much more intuitive: 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 OLS results on the select sample *severely upwardly bias* the returns to criminal capital indicators, which follows because selection into illegal income-generating activity is likely positively correlated with higher earnings. Estimates from the selection corrected models reveal a 76 and 83 percent reduction in the magnitude of the coefficient on the high group for the Heckman and T3T estimates, respectively. All other model coefficients have between a 38 and 51 percent reduction in the magnitude from the OLS point estimate.

In the Heckman and T3T model estimates, we find no returns to either moderate or high experience (both models show a small wage premium for high experience, around 14 percent according to the T3T results, but these estimates fail to approach any conventional level of statistical significance). Very high levels of experience, however, have large and statistically significant returns (an increase in wage rate of around 112 percent). Again though, the incremental change from very high to extreme experience is null (although the change in point estimates is now positive), suggesting increasing but marginally declining returns to criminal experience. Again, this suggests the existence of an experience threshold prior to a wage rate increase. In terms of a specialization premium, the Heckman and T3T estimates imply increases of 32 and 27 percent, respectively, in wage rates. A one-unit increase in the embeddedness measure yields a small return (around 8 percent), although in both models this result is only marginally statically significant. These magnitudes are substantially smaller than the OLS estimates. Finally, note that estimates from both selection models are generally in close agreement, which is a good robustness check.

These results reveal, as is the case with human capital, increasing but marginally declining returns to criminal experience, a wage premium for specialization, and perhaps a small return associated with criminal embeddedness. Moreover, we find strong selection effects that severely bias OLS estimation of returns to criminal capital.

DISCUSSION

In this article, we assessed whether it is theoretically and empirically reasonable to draw a direct parallel between human capital and criminal capital. We considered a number of fundamental concepts associated with human capital theory and mirrored them in the criminal realm. In doing so, we attempted to develop a more theoretically and methodologically comprehensive way to assess returns to investments in criminal capital. Among a sample of serious offending adolescents, we found that criminal capital operated similarly to conventional human capital, to a certain extent, 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. The illegal earnings literature has seldom considered this possibility. There are a number of reasons why the rate of return to investments declines 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 is not as high (Psacharopoulos 1987, 2006). Similar logic would seemingly apply to the illicit economy, which also has strong market features and important competition among some high-volume earners. Future research should continue to explore the illegal earnings–experience profile to better determine the point at which returns to criminal capital begin to decline, as it is an important consideration for policymakers.

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, suggests there is an important socialization aspect to illegal returns and makes the case for the relevancy of criminal networks. Taken together, these results suggest that, through investment in one's own criminal productivity characteristics, an offender likely earns more through illegal means.

Furthermore, our results reveal strong evidence that bias from sample selectivity, if left unaccounted for, dramatically affects 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 in the study of illegal wages and labor supply, we advocate for increased methodological and theoretical rigor borrowed from the rich and well-developed field of labor economics.

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 payoffs per crime than do others, although they did not assess the factors that contributed to the higher payoffs. Our findings suggest that, as in legal work, investment in time, training, and specialization contributes to higher wage rates. This evidence is contrary to Hirschi's (1986:115–16) 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 the training and 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 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 aid in the desistance process. Stronger bonds likely 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). Because our results reveal an ostensible threshold level for returns to criminal experience to become apparent, it is possible that some low experience offenders might 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 draw an analogy to the legal labor market, where, for example, an individual may be dissatisfied with a certain profession, but the investments 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 continues to participate in legal employment, for substantially lower wages. This reflects the centrality of the reservation wage in the problem context. Important determinants, such as having a legal job, risk perception, and drug dependency,

strongly predict which individuals will select into illegal income-generating activities. These findings provide important considerations for reentry 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 respondents who reported selling drugs versus those who did not, there is an enormous difference for respondents who reported selling drugs other than marijuana (around $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. On average this is likely true, but the possibility remains that for some specific crimes, legal and illegal employment may in fact be *complements* instead of substitutes. For instance, Reuter and colleagues (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. We thus suggest that participation decisions in either type of market as a function of wage offers in the other is a question worthy of investigation.

In addition to our measures, there are likely other sources through which one gains criminal capital, such as 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 and colleagues (2009), which may facilitate greater criminal embeddedness. Future research might look into the role institutions play in criminal embeddedness and their impact on the returns to crime.

One possible limitation of our results is our 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 [2003] 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 both the wage offer and productivity indicators, could bias our results. We feel 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.

Criminological research has severely neglected returns to criminal capital, 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, temporarily or permanently, avoid offending.

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Notes

1. See, for example, Mincer (1974), Willis (1986), Ashenfelter and Krueger (1994), Carneiro, Heckman, and Vytlacil (2011).
2. We use the term *criminal capital* to mean the criminal form of human capital.
3. Grogger (1998), too, suggests diminishing marginal returns to crime.
4. In other words, one must be willing to forgo wages in the current period to instead acquire an additional year of schooling or enter job training, which are linked to prospects of higher future earnings or faster wage growth. We credit a helpful reviewer for urging us to develop this particular point.
5. We caution that, although we know of no formal criminological theories that suggest individuals attempt to maximize illegal earnings over their criminal careers, 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.
6. According to Burt (1998) and Coleman (1990), human capital is necessary to succeed but is useless without social relations to gain the opportunities to employ it. Woolcock's (1998:154) discussion of embeddedness and economic development in immigrant communities echoes this: "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."
7. More information regarding the rationale, overall study design, and sample can be found in Mulvey and colleagues (2004) and Schubert and colleagues (2004). For more detailed information on measures and calendar constructs, interested individuals are encouraged to visit the study website (http://www.pathwaysstudy.pitt.edu). Also, all code and syntax used in the present analysis are available upon request from the lead author.
8. 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 a [legal] hourly wage." Acknowledging this practical infeasibility of measuring actual time spent engaged in illegal activity, we settled on defining earnings rate over weeks, as it is the finest level of aggregation possible that 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.
9. The 10 self-reported items include (1) entered or broke into a building to steal something, (2) stole something from a store, (3) bought, received, or sold something that was stolen, (4) used checks or credit cards illegally, (5) stole a car or motorcycle, (6) sold marijuana, (7) sold other illegal drugs, (8) prostitution, (9) took something from another by force, using a weapon, and (10) took something from another by force, without a weapon.
10. Two reviewers independently noted the potentially advantageous role that instrumental violence can play in higher illegal returns. Our measure of experience thus includes income-generating crimes that are concurrent with violence (e.g., taking something by force using a weapon).
11. We considered an imputation strategy using the mean of each individual's observed frequencies at each time period in place of the missing period to generate a cumulative sum. This method produced nearly identical results. Three predictors also had small amounts of missing data: peers, risk perception, and legal job (around 5, 3, and 1 percent, respectively). We retained all of these cases and used mean substitution conditional on participation to account for the missingness.
12. Haynie and Osgood (2005) note that self-reported peer delinquency measures may overestimate the true influence of peers because individuals tend to project their own behavior onto their friends. We feel this is less of an issue in our analysis, because our use 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 that includes offending behavior as a separate regressor.
13. The inverse Mills ratio is the ratio of the standard normal density function, evaluated at $\boldsymbol{\delta}\mathbf{z}_i$, to the standard normal cumulative distribution function.
14. These results are comparable to past findings on illegal earnings. Freeman (1996) found that among a group of Boston youth, occasional offenders and weekly offenders earned $250 and $448, respectively. Viscusi's (1986) survey of inner-city youth from Boston, Chicago, and Philadelphia found an average monthly illegal income of $272. Among a sample of homeless youth in Toronto and Vancouver, McCarthy and Hagan (2001) found participants in the drug trade had average daily earnings of $101.
15. Ideally, we would like to know how the wage rate varies with certain illegal activities. Two things prevent us from doing this, however. First, there is a high degree of overlap in the sample with individuals endorsing multiple crime types, including 80 percent who reported drug selling activity. Second, we are unable to disaggregate the illegal income earned by crime types, meaning we cannot match earnings to specific crimes. However, there is no important difference in mean rate for respondents who reported selling drugs versus those who did not.

16. Based on feedback from a helpful reviewer, we tested additional model specifications to explore the sensitivity of our results to three of our exclusion restrictions. First, including both risk perception and drug dependency in the main equation yields no significant effects of either variable on income, nor did the coefficients on our capital predictors materially change. Also, 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. Detailed results are available in the online supplement (http://asr.sagepub.com/supplemental).
17. 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 $100 * [e^{\beta} - 1]$.

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