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Equal Pay for Equal Work? Considering the Gender Gap in Illegal Pay

Holly Nguyen[1] · Brandy R. Parker[1] · Sally S. Simpson[2]

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Abstract

Objectives To provide quantitative attention to the correlates of the gender gap in illegal pay. Guided by the literatures on the gendered nature of offending, illegal earnings, and the gender gap in legal pay, we ask: what factors are associated with the gender gap in illegal pay?

Methods We use the Delaware Decision Making Study, a sample of incarcerated offenders, to unpack the gender gap in illegal pay with the Blinder-Oaxaca decomposition technique.

Results The gender gap in illegal pay is partly accounted for by criminal analogs—criminal capital and psychosocial attributes—to correlates for the gender gap in legal pay and differences in reward structures. Race also emerges as an important factor.

Conclusions The disadvantage women face in the legal workforce extends to illegal markets, and our understanding about the gender gap in legal pay can be translated to criminal contexts.

Keywords Illegal earnings · Gender and crime · Criminal achievement · Stratification

Introduction

A person's gender remains an important determinant of one's life opportunities (Hausmann et al. 2009). One of the most persistent illustrations of the influence of gender is the pay gap. During the 1960s and 1970s, estimates of the wage gap showed that females earned 40 cents less to every dollar males earned. Since then there has been increasing female labor force participation and a narrowing of the wage gap, with females earning 18 cents less than males (Blau and Kahn 2017). Over the same period, scholars studying gender and crime similarly documented that female criminal earners tend to profit less from crime than their male counterparts, noting that "Just as in the legitimate world, women face discrimination at every stage from selection and recruitment to opportunities for mentoring,

✉ Holly Nguyen
hollynguyen@psu.edu

1 Department of Sociology and Criminology, Pennsylvania State University, University Park, PA, USA

2 Department of Criminology and Criminal Justice, University of Maryland, College Park, MD, USA

skill development, and, especially, rewards" (Schwartz and Steffensmeier 2008:136). However, unlike the research on the gender gap in legal earnings, accounts of the gender gap in illegal pay have largely been theoretical and based on case studies or small ethnographic samples with little quantitative attention paid to unpacking the correlates of the gender gap in illegal pay.

The examination of women and their involvement in crime comes at a critical time. Women now compromise a larger share of the prison population than ever before, with the female prison population standing nearly eight times higher than in 1980. Justice-involved women are among the most marginalized members of society, who tend to be undereducated and unskilled with sporadic employment histories. Sommers and colleagues (2000:76) note that women turn to "crime and illegal hustles for supplementation," while Small (2000:76) contends that "women are motivated to commit crime as a rational response to poverty." Though women may be especially vulnerable to victimization, engaging in and persistence in crime can be a "coping or survival mechanism that is viewed as a necessary or desirable way to meet the many challenges that women offenders face" (Flower 2010:1). It is not surprising that when women turn to crime, they are economically motivated and driven by poverty (Mallicoat 2011). Thus, understanding the returns to crime for these women is essential, as inequality itself may be embedded in economic crime along gender lines. A holistic view of the economic lives and the various ways in which women earn money provides novel information that can inform potential avenues for further theoretical work on women in the illicit market and policy interventions.

The current study addresses the research question: what factors contribute to the gender gap in illegal pay? To guide our research, we turn to the literatures on the gendered nature of offending, illegal earnings, and the gender gap in legal pay to derive expectations regarding gender inequality in the criminal world. Key drivers for the gender gap in legal pay—differences in human capital, occupations, and psychosocial attributes (Blau and Kahn 2017)—have analogs in criminal markets that have been found to vary by gender and to be associated with illegal pay. We analyze data from the Delaware Decision Making Study, which uniquely contains rich information on criminal analogs to popular explanations for the gender gap in legal pay. Using the Blinder-Oaxaca decomposition technique we find that criminal capital, psychosocial attributes, and race are the strongest correlates of the gender gap in illegal pay.

The Importance of the Gender Gap in Illegal Pay

Consistent with the argument that women commit economic crimes to improve their situation but typically earn less than males, it might be easier to shift women away from the illicit economy compared to their male counterparts. In a traditional rational choice model, an individual must choose how much time to allocate between labor (for which they earn income) and leisure to maximize utility gained from consumption and leisure (Becker 1965). Ehrlich (1973) extended the traditional model by allowing individuals to choose to allocate time to crime, which may also net income. According to Ehrlich's (1973:524) model, "the decision to engage in illegal activity is not an inherently either/or choice, and offenders are free to combine a number of legitimate and illegitimate activities or switch occasionally from one to another during any period throughout their lifetime."[1] In this formulation, offending decisions comprise of a rich array of factors beyond things like risks and costs to crime, most notably (potentially forgone) incentives from legal activities. Thus, decisions to offend on the margin encapsulate both legal and illegal incentives. Targeting the legal labor market by decreasing barriers to entry and increasing incentives in the legal market can be an effective strategy for both men and women (Agan and Makowsky 2018). However, if indeed women face disadvantage in *both* legal and illegal markets, policies dedicated to improving legal labor market opportunities for women who engage in economic crimes might be especially promising.

Research suggests that offenders are sensitive to and motivated by monetary rewards from crime (Paternoster and Bushway 2009; Pezzin 1995). For example, using the National Longitudinal Survey of Youth, Pezzin (1995) found that criminal earnings are negatively associated with the probability of desistance. Similarly, Shover and Thompson (1992) found that degree of past success at legitimate and illegal pursuits, and expectations for success with crime were significant predictors of desistance. Paternoster and Bushway's (2009) identity theory of desistance highlights that repeated failure in criminal endeavors is associated with discontentment with the criminal lifestyle. Kerrison et al. (2016) studied the narratives of women attempting to desist from drug use and sex work and found support for the identity theory of desistance, as one of the key motivations for desistance is discontentment with their life. Highlighting the negative and unequal monetary rewards between male and female offenders is one possible lever to motivate females to desist from crime.

Theoretically, understanding differential monetary rewards to crime across genders can inform the literature on the gendered nature of crime and illegal earnings. The literature on the gendered nature of crime emphasizes the contexts, quality, returns to criminal activity, and describes a complex pattern of female participation in crime. Three general perspectives emerge when examining the literature on the gendered nature of offending. One perspective focuses on the reproduction of gender stratification and inequality in the illicit world (e.g., Adler 1993; Cullen and Link 1980; Steffensmeier 1983; Steffensmeier and Terry 1986). Other researchers observe that females advance in crimes that are perceived to be stratified by gender, such as drug selling and shoplifting, by exploiting gender stereotypes to both perpetrate crime and avoid detection (Kruttschnitt 2013; Miller 1995). A more nuanced approach acknowledges structural constraints that shape the ways in which women get involved in crime and how they navigate the criminal world as agentic actors (Sommers et al. 2000).

Numerous studies highlight parenthood and drug addiction as key considerations in studying selection into income-generating crimes. For instance, parenthood is described as a double-edged sword for women at the margins of both legal and illegal worlds. For those who lack access to and the skills necessary to be successful in legitimate work and who feel desperate (Shdaimah and Leon 2015), having dependent children can motivate both offending and desistence (Broidy and Cauffman 2006; Chesney-Lind and Pasko 2006). Substance abuse or addiction may condition these effects. A latent class analysis of soon-to-be-released women in California (Brennan et al. 2012) revealed eight pathways to serious and habitual crime, including two groups of "normal-functioning" but chronic drug-abusing female offenders. One group was comprised predominantly of drug-offending

[1] Others have since built on this concept of time allocation to study criminal choice, including Block and Heineke (1975), Heineke (1978), and Schmidt and Witte (1984).

single mothers while the other was made up of older drug-offending women who were not parenting. A key factor that distinguished the two groups was that the former had more "parenting anxieties" than the latter. According to the authors, "[T]he profile differences suggest a developmental transition linked to a shift in parenting role and differences in parenting stress and age between these otherwise similar pathways (pp. 1495)." Importantly, parenthood and other contextual factors, such as addiction, appear to figure more in decision-making for female than for male offenders (who are less apt to have dependent children living at home with them). In their meta-analysis of 30 studies on the links between drug misuse and crime, Bennett et al. (2008) found a positive connection between substance abuse and a variety of different types of offenses, including robbery, shoplifting, prostitution, and burglary.

Undoubtedly, rich information can be drawn from the structural and decision-making factors associated with why women engage in crime and different offense types. However, there are few studies that attend to the gender gap in illegal pay once women have already entered the illicit market. Research on variation in illegal earnings has predominantly focused on males or has been relatively silent on gender. The few studies that examine illegal earnings by females generally focus on the presence or absence of illegal earnings as opposed to *variation* in illegal earnings. For example, Uggen and Krustchnitt (1998) used the National Supported Work Demonstration project to assess whether the predictors of having illegal earnings varied across males and females and found few differences. Using a sample of 262 incarcerated women, Yule et al. (2015) found that mothers were less likely to be involved in crimes with the potential for monetary returns during months when they lived with their children versus months when they did not (see also Wakefield and Uggen 2004).[2] Our study extends this literature by focusing on whether a pay gap exists between male and female offenders in the illicit market, and if so whether correlates of the gender gap in illegal pay are analogs to correlates of the gender gap in legal pay.

Understanding the Gender Pay Gap

Understanding the correlates associated with the gap is valuable for both policy and theory. Specifically, if the gender gap is associated with gender differences in measurable factors, such as criminal capital or psychosocial factors, variation in illegal pay can present opportunities for early intervention or prevention and reduction in criminal embeddedness. Early interventions, for example, could stifle accumulation of criminal capital and rewards to offending, which has been linked to prolonged criminal careers (Shover and Thompson 1992). Understanding the differential factors associated with a gender pay gap can also add novel commentary to prevention efforts that are based on gendered pathways in and out of

[2] A few exceptions to the focus on the extensive margins are Brady et al. (2015) examination of earnings of female prostitutes in India and Daly's (1989) documentation of gender differences in illegal earnings from white-collar crime. Brady and associates (2015) found that female sex workers with brokers had significantly more customers but significantly lower weekly earnings. They argued that sex workers with brokers were more likely in an exploitative relationship (see also Moffat & Peters, 2004). While Brady et al. (2015) establish that there is variation in illegal earnings among women, their study does not address gender differences in illegal pay. Daly (1989), on the other hand, notes that female white-collar defendants are structurally and demographically less privileged than their male counterparts, translating into less access to organizational resources with which to commit crime and substantially lower economic gains from their attempted crimes.

crime (e.g., Simpson et al. 2008). Female integration into deviant street networks of prostitution, drug sales, and robbery (street pathway) is associated with early offending onset and subsequent accumulation of criminal capital. Other paths, linked to victimization, give rise to non-instrumental expressive crimes. Rather than accumulating criminal capital, offenders have higher levels of mental health problems and illicit drug use—psychosocial factors (see Brennan et al. 2012). Alternatively, opportunities for early intervention may be more difficult if the gender pay gap is explained by unmeasurable "discrimination." It is important to underscore, however, that while the correlates of illegal pay most associated with the gender pay gap are potentially good candidates for policy intervention, they may ultimately not be truly causal determinants of illegal pay.

Theoretically, scholars across various disciplines such as sociology, criminology and economics have looked to concepts and processes studied in the legal labor market to better understand the involvement in and nature of economic crime (Holzman 1982; Letkemann 1973; Loughran et al. 2013a, b; Steffensmeier and Ulmer 2005; Sutherland 1937). Scholars who adopt a "crime as work" perspective contend that processes involved with understanding criminal behavior are not fundamentally different from conventional behaviors. Therefore, drawing on the established literature on the gender gap in legal pay can be a useful starting point and provide insight into the similarities and differences in gender pay gaps in legal and illegal markets.

While there are similarities between the legal and illegal markets, the gender gap in illegal pay can shed light on the potential differences. Compared to the legal market, the illegal market operates covertly and is even more socially regulated. That is, transactions are not enforceable through the legal system and rely on informal resolutions. This informal regulation may exacerbate gender inequalities in a male dominated arena—such drug trafficking (Rodriguez and Griffin 2005) or even sex work, where males typically control the streets (Maher 1997; Maher and Curtis 1998; see also Logan's study of male sex work 2010), robbery (Miller 1998) and fraud (Daly 1989; Steffensmeier et al. 2013). However, barriers to entry in the illegal market, especially for lower level offenses, are very low (Reuter 1983). Additionally, sellers set the market price for illegal commodities, which can vary across transactions. This can essentially bypass some of the institutional barriers to illegal pay disparity. Generally, illegal transactions are inconsistent and intermittent compared to stable legal wages.

Criminal Capital

One of the traditional correlates of the gender gap in legal pay is gender differences in human capital (Mincer and Polachek 1974). Studies have shown that some of the most decisive factors that determine competitiveness in the workforce are education, skills, and productivity. Human capital can be attained through formal education and informal on-the-job training (Schultz 1961). Using the Panel Study of Income Dynamics, Blau and Kahn (2017) found that human capital factors (i.e., education and experience) accounted for 27 percent of the gender gap in legal pay in 1980 compared to only 8 percent in 2010. Over time, women have become more educated and now comprise a larger share of the legal workforce. Although growth in female formal education is associated with the narrowing of the pay gap, less time in the labor force remains an important explanation in understanding women's career prospects over the life course (Goldin 2008). Manning and Swaffield (2008) show a substantial human capital impact on gender inequality, but this is the result of differences in on-the-job training. Similarly, formal education modestly explains disparities in pay among the self-employed; however, gender differences in work experience contribute substantially to earnings differentials (Bates 1990).

The advantage of criminal skills and experience, or criminal capital, has been observed in both ethnographic and quantitative work and across a number of offense types including robbery (Wright and Decker 1994), burglary (Letkemann 1973; Shover 1985), and drug selling (Sullivan 1989; Padilla 1992). For example, Loughran et al. (2013a; b) found that criminal experience and offense specialization were positively associated with criminal earnings. Similar to females in the legal labor market, female offenders tend to have less experience and are more intermittent in their offending—perhaps due to Anderson's (2005) observation that women's agency and experience gained in the illicit market empower her to transition back into future conventional work more readily than males. The duration of criminal careers of women are considerably shorter and less experienced than men (Mazerolle et al. 2000; Block et al. 2010), and it is more common for women to start offending in adulthood (Eggleston and Laub 2002; Simpson et al. 2016) and to offend much less frequently (Brame et al. 2004; Wikström 1990). Collectively, this line of research suggests that females generally have lower levels of criminal capital than males. Thus, similar to the role that human capital, in the form of experience, plays in the gender gap in legal pay, gender differences in criminal capital may be associated with a gender gap in illegal pay. In fact, experience in criminal markets may be more influential than human capital in legal markets because there are no formal criminal education credentials.

Crime Types

The gender gap in legal pay has also been attributed to gendered preferences. Males and females both self-select and have differential access into particular occupations, with males tending to be more tolerant of undesirable job characteristics (Kilbourne et al. 1994). Occupations preferred and dominated by women tend to be more flexible but lower status, pay, and risk, whereas males tend to prefer manual labor over the service sector, which has a different wage distribution (Budig and England 2001). The theory of compensating differentials predicts that if unskilled workers are tolerant of unappealing job characteristics, such as dangerous conditions, then such jobs will offer a wage premium (Smith 1979). DeLeire and Levy (2004) provide evidence that on average women are more risk averse than men and choose safer occupations. Female entrepreneurs are also more likely to be self-employed in lower paying industries, whereas males are more likely to be in higher paying industries (Hundley 2001).[3] Yet, even when males and females are engaged in similar entrepreneurial work with maximum flexibility (such as driving for Uber or Lyft), there is still a gender wage gap. In their recent study, Cook e al. (2020) uncovered a 7 percent gender gap in pay in the gig economy. Essentially, they find that this gap is associated with gender-based preferences/constraints, including returns to experience, a pay premium for faster driving, and differences in driving locations (e.g., closer to home).

Like the unequal distribution of gender across occupations in legal markets, males and females make up differential proportions of types of crime. Crimes that might result in violence, like robbery, tend to be male dominated. Much of female crime clusters around minor property crimes and drug offenses. For example, in 2012 females made up over a

[3] Evidence shows that when men and women work in the same job-cell (i.e., within occupation, within employer) they earn similar wages but, typically, integration is rare (Groshen 1991).

quarter of all arrests, but only 13 percent of the arrests for robbery. Conversely, females contributed to roughly 40 percent of the arrests for larceny-theft, forgery, fraud and embezzlement (Uniform Crime Reports 2013). These patterns suggest differential access to crime types and/or gendered preferences in crime types. Prior research has demonstrated variation in earnings across crime types (Nguyen and Loughran 2017). If women tend to sort into crimes that are typically lower paying, it is possible that like compensating differentials in legal markets, compensating differentials in illegal markets is associated with a gender gap in criminal earnings.

Psychosocial Attributes

A newer line of research investigates gender differences in psychosocial attributes between males and females in both selection into occupations and industries and differences in legal wages. These attributes can be considered "soft skills" and include non-cognitive skills and personality traits (Heckman and Kautz 2012). Overall research suggests that personality traits such as risk seeking, self-esteem, locus of control and self-confidence are more characteristic of males than females and explain a small portion of the gender gap in legal pay (e.g., Blau and Kahn 2017; Manning and Swaffield 2008; Nyhus and Pons 2012).

Criminological work has also highlighted that psychosocial attributes, such as self-control, vary across gender (e.g., Burton et al. 1998; LaGrange and Silverman 1999), and traits such as impulsivity and low self-control are positively associated with variation in illegal earnings (Morselli and Tremblay 2004). Correspondingly, criminal self-efficacy is associated with greater returns to crime (Laferriere and Morselli 2015) and negatively with intentions to desist (Brezina and Topalli 2012). Relatedly, desire for wealth is associated with more illegal pay (McCarthy and Hagan 2001), and overconfidence is also associated with a higher probability of offending (Loughran et al. 2013a, b). Criminal psychosocial attributes may be associated with a gender gap in illegal pay given variation by gender and illegal earnings. Because the rewards to crime, and earnings in particular, are generally more immediate than the returns to a legal job, the influence of psychosocial attributes may be heightened in criminal markets.

In sum, many of the key drivers of the gender gap in legal pay—human capital, occupations, and psychosocial attributes—have analogs in the illegal market that have been found to differ across gender as well as variation in illegal pay. We expect that these criminal analogs are also correlated with the gender gap in illegal pay.

Data and Measures

The Delaware Decision Making Study offers a unique opportunity to examine the gender gap in illegal pay. First, we are able to use three distinct samples from the DDMS—an incarcerated sample that do not report illegal pay ("non-earners"), and an incarcerated sample that report illegal pay ("earners"), and a sample of community members for descriptive comparison ("community"). Second, the DDMS contains questions specifically designed to capture illegal pay and variation in illegal pay by crime type, which is similar to the within occupation approach used in studies that examine the gender gap in legal pay. Third, illegal pay is often confounded with the frequency of offending, especially over a long time period. This increases measurement error and makes it difficult to compare illegal pay across gender. Conversely, the DDMS respondents reported what s/he earned for a "typical" crime across four different crime types, making the units more comparable across respondents. Finally, the DDMS contains an adequate number of observations of illegal pay among females. Generally, there is a dearth of data sources that incorporate measures of illegal pay. Information on illegal pay for females is even scarcer.

Incarcerated Sample

The DDMS incarcerated sample consists of a total of 511 unique respondents (395 males and 116 females) who as of 2016 were incarcerated at one of three pre-release facilities in Wilmington and New Castle, Delaware (two male facilities, one female facility), or who were recently released from prison and on Level 3 parole in Delaware. Subjects were within 30 days of release from the facility or were within 60 days of starting parole. Recruitment took place at a pre-release center and at two parole offices in Delaware. A list of persons approaching 30 days pre-release or who had been placed on Level 3 parole within the past 60 days was provided to the research team by the Delaware Department of Corrections. Researchers visited the potential subjects in prison or the parole office, explained the study, and inquired whether they would like to participate. Researchers reviewed the purpose of the study and discussed the consent process and voluntary nature of the study. Data were collected in group settings in a multipurpose room at the work release center or in a conference room at the parole office. The questionnaire was self-administered, but researchers read the questions and response categories out loud and remained in the room to answer any questions or address any problems. The questionnaire took approximately 60 min to complete. Subjects who completed the questionnaire received $10 for participating.

Community Sample

The research team also recruited a comparison sample from the community. Screened out for previous criminal convictions (see below), most included in the sample also did not report engaging in crime. Advertisements were posted on the University of Delaware campus, in local libraries in Wilmington and New Castle, as well as other public bulletin boards (e.g., Panera Bread, local YMCAs, union halls). Potential participants called a phone number, which connected them to a research office at the University of Delaware. During the initial conversation, a researcher explained that the study was about decision making among adults and confirmed that the potential subjects were 18 years of age or older and had not been convicted of a non-traffic offense. If the subjects met these criteria and were interested in participating, s/he was scheduled an appointment at the University of Delaware campus where subjects signed a consent form and then completed the self-administered questionnaires with a researcher present to answer any questions or address any problems. The questionnaires were anonymous with no unique identifying information collected and took approximately 60 min to complete. Subjects who completed the questionnaire were compensated $50 for their time. The community sample consists of 156 respondents, 71 male and 85 female. It is important to highlight that the recruitment and sampling procedures were very different between the community sample and the incarcerated. While it is interesting to look at descriptive differences, direct comparisons should not be made.

Measures

Illegal Pay: Participants were asked "Have you ever participated in a robbery?" If s/he provided an affirmative answer, s/he was asked "How much money did you make from a typical robbery?" The same questions were asked for burglary, drug dealing and forgery/fraud. Few respondents in the community sample reported engaging in the aforementioned crime types. Thus, illegal pay cannot be estimated for the community sample. However, 279 males and 65 females answered affirmative to one or more of the four economic crimes, resulting in 506 male and 123 female observations of illegal pay. Among "earners," males on average report making $1,152.85 and females report making $671.82 across the four crime types.[4]

Race/Ethnicity: Participants were asked "What race/ethnicity do you identify with most?" The choices included Caucasian, African-American, Hispanic/Latino, Asian-American and Other. We collapse race into three categories: white, black, and Hispanic/other. There are significant differences in the distribution of race/ethnicity across genders and samples. Whites comprise a lower proportion of respondents in the community sample compared with the incarcerated sample. Within the incarcerated sample, whites compromise a lower proportion of "non-earner" illegal pay observations versus "earner" observations.

Criminal Capital: *Age at first crime* is derived from the question "How old were you when you first got involved in committing crime?" In the incarcerated sample, males report being younger when committing their first crime than females among "non-earners" (males = 16.39, females = 18.13) and "earners" (males = 13.97, females = 17.02). Additionally, "earners" report an earlier age at first crime than "non-earners". *Number of arrests* is derived from the question "How many times were you arrested as an adult?" Males tend to have a more extensive arrest history than females. We also see the fewest average number of arrests in the community sample (males = 1.75, females = 1.00). Though the difference from the community sample is less pronounced, "earners" (males = 8.30, females = 7.81) tend to have more arrests than "non-earners" (males = 5.71, females = 6.38). *Specialization* is a count of the different crime types the participant reports taking part in. Among "earners", both males and females report engaging in approximately two of the four crime types queried about.

Crime Types is a binary indicator with 1 = the participant reported participating in the specific offense (i.e., robbery, burglary, drug selling, fraud/forgery) and 0 = did not engage in the specific offense. While male and female "earners" are similarly involved in burglary and drug selling, males tend to be more involved in robbery while females tend to be more involved in forgery/fraud.

Psychosocial Attributes: *Risk Preferences* is a factor consisting of 6 items (loadings 0.57-0.80, Eigenvalue = 3.00), including items such as "Riding in a car driven by someone who had been drinking" and "Trying a new drug that you know nothing about." Participants were asked how each statement reflects himself /herself and to provide an answer from a 4 point Likert scale (1 = Rarely/Never, 2 = Occasionally, 3 = Often, 4 = Almost Always/

[4] How reliable is self-reported illegal pay? Extant research suggests that validity and reliability of self-reported illegal pay is good (e.g., Charest 2004; Morselli and Tremblay 2004). Most recently, Nguyen and Loughran (2017) analyzed the validity and reliability of self-reported illegal earnings using the Pathways to Desistance study and the National Supported Work project. The authors reported generally good validity and reliability of self-reported illegal earnings across the two datasets.

Always). In general, males report higher risk preferences than females. Risk preferences are lowest in the community sample (males = -0.23, females = -0.36) and highest among "earners" (males = 0.25, females = 0.06). *Impulsivity* is a factor consisting of 8 items (loadings 0.53 to 0.68, Eigenvalue = 2.92) such as "I would like to explore strange places…I prefer friends who are excitingly unpredictable." Participants were asked to indicate which of the choices most describes his/her likes or the way s/he feels (1 = Strongly Disagree, 2 = Disagree, 3 = Agree, 4 = Strongly Agree). Respondents in the community sample are the least impulsive and earners are the most impulsive. While there were little differences in impulsivity across gender for "non-earners" (males = 3.45, females = 3.49) and "earners" (males = 3.75, females = 3.71), females in the community sample report being less impulsive than the males (males = 3.29, females = 2.99). *Planfulness* is a factor consisting of 6 items (loadings 0.57 to 0.66, Eigenvalue = 2.22) such as "I plan tasks carefully… I am a careful thinker." Participants were asked how s/he feels or what best describes him or her to provide an answer from a 4 point Likert scale (1 = Rarely/Never, 2 = Occasionally, 3 = Often, 4 = Almost Always/Always). In the community sample, male and female respondents report being similarly planful (males = 3.72, females = 3.75). However, in the incarcerated sample males report being more planful than females. This is true for both "non-earners" (males = 3.41, females = 3.33) and "earners" (males = 3.39, females = 3.09).

Table 1 displays the descriptive statistics for our three samples: the incarcerated "non-earners", the incarcerated "earners" and the "community" sample. Because the illegal pay measure was asked for four crime types (robbery, burglary, drug selling, fraud/forgery), we nested each crime type within person, where each person could potentially contribute up to four observations. Given that most respondents do not report earning illegal pay for all four crime types, we have an unbalanced panel of 506 observations across 279 males and 123 observations across 65 females that constitute the "earners" sample. The incarcerated "non-earners" sample consists of 1074 observations across 379 males and 341 observations across 109 females.

As shown in Table 1, males report earning more than females across all four crime types.[5] There are differences across samples (i.e., incarcerated "non-earners", incarcerated "earners", and "community") and genders in criminal capital, crime types, and psychosocial attributes. We highlight several points. First, incarcerated males report more criminal capital than incarcerated females, as evidenced by younger age at first crime and more arrests. Among the incarcerated, male "earners" report more criminal capital than male "non-earners". The distinction in criminal capital between female "non –earners" and female "earners" is not as pronounced. Second, incarcerated "earners" report similar levels of specialization across the four crime types, though males tend to be more involved in robbery while females tend to be more involved in forgery/fraud. This suggests differential sorting into different crime types.[6] Moreover, there are differential returns to the four income-generating crime types that vary by gender. Third, males report a greater preference for risk and somewhat higher levels of impulsivity than females. For both males and females, the community samples report having the least preference for risk, while the incarcerated "earners" report the greatest preference for risk. We observe a similar pattern for impulsivity. Finally, male and female community members report being similarly

[5] We observed a gender gap in illegal pay across four other data sources (see Fig. 1 and Table 6 in "Appendix A").

[6] Table 7 in "Appendix B" displays the descriptive statistics for males and females in the incarcerated sample by each of the four crime types.

Table 1 Descriptive statistics of delaware decision making sample

	Males			Females		
	Incarcerated sample			Incarcerated sample		
	Non-earners	Earners	Community	Non-earners	Earners	Community
	n = 1074 obs 379 ppl	n = 506 obs 279 ppl	n = 71 ppl	n = 341 obs 109 ppl	n = 123 obs 65 ppl	n = 85 ppl
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Illegal Pay (log dollars)						
All	–	7.05 (2.22)		–	6.51 (1.92)	–
Robbery	–	7.33 (2.32)		–	6.92 (1.73)	–
Burglary	–	7.35 (1.94)		–	6.83 (1.13)	–
Drug Selling	–	6.63 (2.22)		–	6.29 (1.90)	–
Fraud	–	7.66 (2.25)		–	6.32 (2.52)	–
A. Race/ethnicity						
White	0.40 (–)	0.50 (–)	0.32 (–)	0.60 (–)	0.75 (–)	0.24 (–)
Black	0.50 (–)	0.40 (–)	0.61 (–)	0.36 (–)	0.23 (–)	0.65 (–)
Hispanic or Other	0.10 (–)	0.11 (–)	0.07 (–)	0.04 (–)	0.02 (–)	0.12 (–)
B. Criminal capital						
Age First Crime	16.39 (7.19)	13.97 (4.09)	–	18.13 (5.68)	17.02 (6.02)	–
Number of Arrests	5.71 (5.67)	8.30 (7.40)	1.75 (1.00)	6.38 (6.21)	7.81 (7.07)	1.00 (–)
Specialization		2.31 (1.01)	–		2.45 (1.10)	–
C. Crime types						
Robbery	0.22 (–)	0.22 (–)	0.03 (–)	0.17 (–)	0.21 (–)	–
Burglary	0.21 (–)	0.23 (–)	0.04 (–)	0.11 (–)	0.15 (–)	–
Drug Selling	0.54 (–)	0.45 (–)	0.15 (–)	0.47 (–)	0.42 (–)	0.01 (–)
Forgery/Fraud	0.12 (–)	0.10 (–)	0.04 (–)	0.21 (–)	0.21 (–)	–
D. Psychosocial attributes						
Risk Preferences	0.11 (1.12)	0.25 (1.07)	−0.23 (0.80)	−.16 (0.79)	0.06 (0.90)	−0.36 (0.64)
Impulsivity	3.45 (0.98)	3.75 (0.72)	3.29 (0.71)	3.49 (0.75)	3.71 (0.78)	2.99 (0.78)
Planfulness	3.41 (1.12)	3.39 (0.77)	3.72 (0.63)	3.33 (0.70)	3.09 (0.72)	3.75 (0.61)

planful. Yet among the incarcerated, there was little difference between male "non-earners" and male "earners" in terms of being planful, while incarcerated female "earners" report being less planful than female "non-earners."

Blinder: Oaxaca Demcomposition

The Blinder-Oaxaca counterfactual decomposition technique is often used to study mean outcome differences between two groups (Blinder 1973; Oaxaca 1973). It separates pay differentials into two components: a portion that arises because males and females, on average, have different characteristics (e.g., criminal capital) when both groups receive the same treatment (explained component), and a portion that arises because one group is favored over the other given the same individual characteristics (unexplained component). To be clear, the term "explained" refers to the group differences accounted for by the covariates in the model and does not suggest any causal effects. The two portions, called endowments and coefficients effects, provide the foundation of the Blinder-Oaxaca decomposition. The coefficients effect is traditionally interpreted as a measure of discrimination.

$$R = E\left(Y_m\right) - E(Y_f) \tag{1}$$

Given there are two groups, males and females, an outcome variable Y, (log) pay and a set of covariates (e.g., criminal capital, crime types, psychosocial attributes), the question is how much of the difference in illegal pay gap is accounted for by differences between males and females in the covariates. Where E(Y) is the expected value of (log) pay.

The Blinder-Oaxaca technique is based on the linear models: the first for males and the second for females:

$$Y_m = X_m B_m + u_m \tag{2}$$

$$Y_f = X_f B_f + u_f \tag{3}$$

Let Y be log of illegal pay, X be a vector of variables (e.g., criminal capital, crime types, psychosocial attributes), B be a vector of coefficients and u be the error term.

In order to examine correlates of illegal pay differentials between males and females, we estimate a counterfactual equation where females are treated as males. In other words, the intercept and coefficients in the female equation are replaced by those in the male equation. The counterfactual equation becomes

$$R = \left\{E\left(X_m\right) - E\left(X_f\right)\right\}'\beta_f + E\left(X_f\right)'\left(\beta_m - \beta_f\right) + \{E\left(X_m\right) \tag{4}$$

The outcome is comprised of two components.

$$R = E + C$$

The first component

$$E = \left\{E\left(X_m\right) - E\left(X_f\right)\right\}'\beta_f$$

is often referred to as the "endowments" (E) component and derives the difference in group means for the vector of regressors. It is similar to the counterfactual: if a female had the endowments of males, what would her illegal pay be?[7] The second component

$$C = E\left(X_f\right)'\left(\beta_m - \beta_f\right)$$

is referred to as the "coefficients" (C) component and highlights the differences in coefficients between the two groups. It provides a counterfactual: if a female had her own endowments but was in a male reward structure, what would her illegal pay be? Ideally, the reward structures should be the same. Any discrepancies could be attributed to "discrimination."

It is important to note that the "discrimination" component is the unexplained component after accounting for observables in the data. The unexplained component could

[7] Note that even though the word "counterfactual" is commonly used when describing the method, it does not connote causation.

Table 2 Decomposition models of income-generating crimes in incarcerated sample (n = 511 ppl)

Variables	Log Points	Exp(b)	%
Panel A			
Males	0.30	1.36	
Females	0.25	1.28	
Total Gap	0.05	1.05	
Endowments	− 0.04	0.96	
Coefficients	0.62	0.10	
Interaction	0.10	1.10	
Panel B			
B. Criminal Capital	0.02	1.02	50
C. Psychosocial Attributes	0.01	1.01	25
			100
Total Explained	0.04	1.04	67
Total Unexplained	0.02	1.02	33
Total Gap	0.06	1.06	100

over-estimate discrimination as it does not account for any unavailable correlates in the data. However, it could also under-estimate discrimination because acquisition of criminal capital or selection into differential crime types can be a downstream product of prior discrimination. We underscore that the Blinder-Oaxaca counterfactual decomposition is a descriptive technique and caution against causal interpretations of the results.

Results

We begin by examining the gender gap in the probability of reporting participating in any income-generating crime across individuals in the incarcerated sample.[8] Table 2 displays the results of the decomposition model for linear probability models in which 1 = engaging in at least one of the income-generating crimes (robbery, burglary, drug dealing, forgery) and 0 = no income-generating crimes. Overall, there is a gender gap of only approximately 5 percentage points in the probability of engaging in income-generating crime among the respondents in the incarcerated sample. Panel A presents the endowments and coefficients portions of the decomposition model. The endowments show that if a female had the characteristics or "endowments" of a male but remained in her own reward structure, her probability of engaging in income-generating crime would actually decrease by 4 percentage points. Alternatively, if a female with her own characteristics was placed in the male reward structure, her probability of engaging in income-generating crime would increase

[8] As shown in Table 8 of "Appendix C", age of first crime is inversely associated with reporting affirmative to one or more income-generating crime among males but not females, though the association is weak. Number of arrests and impulsivity are positively associated with reporting having engaged in one or more income-generating crime for both males and females. However, number of arrests is weakly associated for both genders and is marginally significant for females. As such, there does not appear to be much selection into reporting any illegal pay among either males or females based on observables.

by 10 percentage points. These results are suggestive that the gender gap in participation in income-generating crime is very small and largely accounted for by observable correlates.

Panel B reports the results of the decomposition model partitioned into explained and unexplained components. The factors are separated into the categories of correlates: race/ethnicity, criminal capital[9] and psychosocial attributes. Overall, our model is able to account for approximately 67 percent of the observed gender gap in participating in income-generating crimes, with 33 percent left unexplained. Race/ethnicity and psychosocial attributes each account for 25 percent of the gender gap in income-generating crime participation. Criminal capital accounts for 50 percent of the gap. However, we underscore that the total gender gap in participating in income-generating crime among the incarcerated sample is only 5 percent.[10] In sum, Table 2 highlights that there are few gender differences between reporting no income-generating crime and at least one income-generating crime.

Turning attention to the pay gap, Table 3 displays the results of the nested female and male wage equations. For the male equation, non-white subjects report higher illegal pay. Black females also report higher illegal pay than white females. Our criminal capital measures do not predict illegal pay in the male equation, while age at first arrest is inversely associated with illegal pay in the female equation. A one year decrease in the age at first crime is associated with a 10 percent increase ($p<0.01$) in illegal pay. Specialization does not emerge as significantly associated with illegal pay for either gender. For males, compared to robbery, a typical drug sale is 66 percent less lucrative ($p<0.05$) whereas forgery is 57 percent more lucrative ($p<0.10$). For females, a typical drug transaction is associated with an 89 percent lower ($p<0.10$) illegal pay compared to a typical robbery. Though risk preferences and impulsivity do not emerge as significantly predictive of illegal pay for either gender, a one unit increase in being planful is associated with a 38 percent increase ($p<0.01$) in illegal pay among males but does not emerge as a significant predictor for illegal pay for females. Overall the results reveal that different factors affect prosperity for males and females in the DDMS. The non-white premium on illegal pay, for both males and females, is unexpected and contrary to what is observed in the legal labor market (Mandel and Semyonov 2016).[11]

Table 4 displays the results of the decomposition model for the ordinary least squares estimator. Males' estimates of illegal pay are $1,156 and females' estimates are $675, making the estimated illegal pay gap $481. Panel A presents the endowments and coefficients portions of the decomposition model. The endowments show that if a female had the characteristics or "endowments" of a male but remained in her own reward structure, her illegal

[9] Criminal capital includes age first crime and number of arrests. Specialization was omitted from the income generating crime decomposition.

[10] Detailed linear probability models by gender are presented in Table 8 "Appendix C". Overall, criminal capital measures (age first crime and number of arrests) are significantly related to the probability of reporting income generating crimes among males. Impulsivity is significantly related to the probability of reporting income generating crimes among males and females.

[11] Since not all subjects participated in one or more of the four economic crimes queried about, we observe illegal pay for only a subset of the incarcerated sample. Estimating illegal pay only for those who choose to engage in income-generating crime could possibly lead to a nonrandom sample and biased estimates. We address the problem of sample selectivity bias in estimating illegal pay by using the Heckman (1979) two-equation model where selection can be treated as a form of omitted variable bias. We present our results in "Appendix D". As Table 10 shows, the gender gap in participating in income-generating crimes in the incarcerated sample is small. The results of the Heckit models are substantively similar to the ones presented here.

Table 3 Ordinary least squares regression models predicting illegal pay (log)

	Males		Females	
	(n = 506 obs; 279 ppl)		(n = 123 obs; 65 ppl)	
	B	Robust SE	B	Robust SE
A. Race/Ethnicity				
Black vs. White	0.97***	0.21	0.92*	0.46
Hispanic and Other vs. White	0.98**	0.32	− 0.12	1.15
B. Criminal capital				
Age First Crime	− 0.01	0.02	− 0.10**	0.04
Number of Arrests	0.00	0.01	− 0.02	0.03
Specialization	0.01	0.10	− 0.09	0.18
C. Crime types				
Burglary vs. Robbery	0.25	0.28	− 0.24	0.57
Drug Selling vs. Robbery	− 0.66*	0.25	− 0.89[a]	0.48
Forgery vs. Robbery	0.57[a]	0.36	− 0.66	0.53
D. Psychosocial attributes				
Risk preferences	− 0.08	0.09	0.25	0.22
Impulsivity	0.06	0.14	− 0.24	0.28
Planfulness	0.38**	0.13	0.31	0.25
Constant	5.34***	0.91	8.83***	1.88

[a] $p < .10$ * $p < .05$ ** $p < .01$ *** $p < .001$

pay would increase by 83 percent. Alternatively, if a female with her own characteristics was placed in the male reward structure, her illegal pay would increase by 26 percent. These results are suggestive that endowments make up more of the gender gap in illegal pay than differences in reward structures. That is, observables explain a greater portion of the pay gap than unobservables.

Panel B reports the results of the decomposition model partitioned into explained and unexplained components. The factors are separated into the categories of explanations: race/ethnicity, criminal capital, crime types and psychosocial attributes. Overall, our model is able to explain approximately 73 percent of the gender gap in illegal pay in the DDMS, with 27 percent left unexplained. Criminal capital and psychosocial attributes account for 23 percent and 26 percent of the gender gap in illegal pay, respectively. Contrary to the importance of differential occupations to the explanation of the legal gender pay gap, crime types, or differential occupations, do not help explain the gender gap in illegal pay, at least among the crime types examined. Unexpectedly, race/ethnicity accounts for 59 percent of the explained variation. We investigate how gender intersects with race in Table 11 "Appendix E", which shows the unadjusted pay gap in the DDMS incarcerated sample.

Table 4 Decomposition models of the illegal gender pay gap (n = 629 observations; 344 ppl)

Variables	Log Points	Exp(b)	%
Panel A			
Males	7.05	$1156	
Females	6.51	$675	
Total Pay Gap	0.54	1.71	
Endowments	0.60	1.83	
Coefficients	0.23	1.26	
Interaction	− 0.30	0.74	
Panel B			
A. Race/Ethnicity	0.23	1.26	59
B. Criminal Capital	0.09	1.10	23
C. Crime Types	−0.03	0.97	− 08
D. Psychosocial Attributes	0.10	1.11	26
			100
Total Explained	0.39	1.48	73
Total Unexplained	0.14	1.15	27
Total Pay Gap	0.54	1.71	100

Supplemental Analysis: American Community Survey

To provide descriptive context on the gender pay gap in the legal labor market in Delaware at approximately the time of the DDMS data collection period, we turn to the American Community Survey (ACS) Public Use Microdata Sample (PUMS) 2012–2016 5-year estimates. PUMS is a subsample of ACS respondents for which individual-level information is publicly available, with 5-year estimates covering approximately 5 percent of the population.[12] For our analyses, we restrict our analytic sample to respondents that worked 50–52 weeks during the past 12 months (over 80% of the employed sample), which was necessary given that the public use data offers only broad categories of weeks worked during the past 12 months.[13] As the number of weeks worked decreases, the range for the number of weeks worked increases. This hinders our ability to accurately calculate a weekly wage. We note, however, that the gender representation of each of the categories were comparable in that females were not overrepresented in the fewer weeks worked in the past 12 months categories. Our analytic sample consists of 16,335 year-round workers—8296 males and 8,039 females.

We approach the analyses of the ACS with a similar strategy as we do with the DDMS; however, our measures in the ACS are more limited. We account for average weekly pay, age, education, race/ethnicity, average hours per week in the past 12 months, industry (construction, manufacturing, warehouse/transportation, retail, and other services), and secondary occupations. Detailed description of the measures is available in "Appendix F".

[12] PUMS data can be downloaded from the United States Census Bureau website at: https://www.census.gov/programs-surveys/acs/data/pums.html.

[13] Category for weeks worked during past 12 months:0 = N/A (less than 16 y/o or did not work during past 12 months); 1 = 50 to 52 weeks; 2 = 48 to 49 weeks; 3 = 40 to 47 weeks; 4 = 27 to 39 weeks; 5 = 14 to 26 weeks; 6 = 14 weeks or less.

Table 5 Decomposition models of the gender pay gap in legal pay—ACS

Variables	Full Sample (n = 16,335 ppl)		%	Key Industries[a] (n = 5,552 ppl)		%
	Log Points	Exp(b)		Log Points	Exp(b)	
Panel A						
Males	6.8	$900		6.72	$826	
Females	6.53	$687		6.32	$557	
Total Pay Gap	0.27	$213		0.39	$269	
Endowments	− 0.09	0.91		0.04	1.04	
Coefficients	0.31	1.37		0.32	1.38	
Interaction	0.04	1.04		0.03	1.03	
Panel B						
A. Race/Ethnicity	0.01	1.01	0.14	0.00	1.00	0.00
B. Age	− 0.00	1.00	0.00	0.01	1.01	0.05
C. Education	− 0.03	0.97	− 0.43	− 0.02	0.98	− 0.09
D. Weekly Hours	0.11	1.12	1.57	0.16	1.17	0.76
F. Industry Types	0.01	1.01	0.14	0.07	1.07	0.33
G. Secondary Occupations	− 0.03	0.97	− 0.43	− 0.01	0.99	0.05
			100			100
Total Explained	0.07	1.07	26	0.21	1.24	54
Total Unexplained	0.2	1.22	74	0.18	1.2	46
Total Pay Gap	0.27	1.31	100	0.39	1.48	100

[a]Key industries include construction, manufacturing, retail, transportation warehouse, and service

We estimate the Blinder-Oxaca decomposition technique with two samples: (1) the full sample of respondents who worked 50–52 weeks across all industries and (2) a sub-sample of respondents who worked 50–52 weeks in five key industries that individuals who have criminal justice contact are likely to work in (i.e., construction, manufacturing, retail, transportation warehouse, and service; see Bushway et al. 2007). The results of our decomposition model are illustrated in Table 5.[14]

As shown in Table 5, we observe a gender gap in legal pay of $213 and $269 for the full and the restricted samples of year-round workers, respectively. Among the full sample, the model explains approximately 26 percent of the gap, which is mostly accounted for by gender differences in average weekly hours, industry types, and race/ethnicity. When restricted to the five key industries, the model explained 54 percent of the pay gap. The majority of this explained component is accounted for by gender differences in average weekly hours and industry types.

[14] The OLS estimates are available in Table 13 in "Appendix F". Results are as expected: age, education, and the average hours worked per week are positively associated with weekly wages. Respondents who are black earned less weekly than respondent who are white or other race/ethnicity. Those in retail and service industries and in secondary occupations also earned lower wages. Overall, the results are similar for both genders.

Given that we are not able to account for sample selection into the legal labor market nor selection between full-time versus part-time with the ACS data and the decomposition method is a descriptive method, we caution any generalizations or causal interpretation of the results. Nonetheless, our findings provide us with a cursory view of the legal labor market in Delaware. We explore potential implications of the double disadvantage that the women face in both the legal and illegal labor markets in our discussion section.

Discussion

Our study was inspired by the dearth of research on the correlates of the gender gap in illegal pay. Overall, our Blinder-Oaxaca decomposition analysis was able to explain 73 percent of the gender gap in illegal pay in the DDMS, suggesting that the majority of the gap is due to "endowments" or gender differences in measureable factors. The 27 percent unexplained component is traditionally interpreted as a measure of discrimination. Specifically, if a woman remained in her own reward structure but had the endowments of males, her illegal pay per crime would increase by about 83 percent. Yet if placed in the male reward structure, a woman with her own endowments would increase her earnings by slightly more than 26 percent. This suggests that if discrimination in criminal markets influences the gender gap in illegal pay, it primarily does so through its impact on endowments, or the characteristics that differentiate male and female offenders. While these differences may partly reflect structural inequality in criminal markets, they also provide guidance on potential avenues for intervention and rehabilitation.

For example, our criminal capital variables accounted for 23 percent of the gender gap in illegal pay. Consistent with past literature, male offenders reported an earlier age of onset, which some scholars argue may be the best predictor of the future course of a criminal career (Blumstein et al. 1985; Wolfgang et al. 1972). However, few studies have examined age of onset and variations in illegal earnings. Interestingly, onset age was associated with illegal pay among females but not males. Females who reported engaging in criminal behavior at an earlier age reported higher illegal pay. This aligns with studies that find that criminal experience is an important determinant of illegal pay (e.g., Loughran et al. 2013a, b) and contrasts Hirschi's (1986) depiction of the criminal career: "[crime] does not appear to be a career of increasing skill and sophistication, but rather one that… starts with little of either and goes downhill from there" (pp. 115). This suggests that early intervention that inhibits accumulation of social and human criminal capital may be especially important for females.

Differential industries, or occupational sorting, has been a dominant explanation of the gender gap in legal pay (Heckman et al. 2006). We similarly observed that differential participation in industries explained some of the gender gap in legal pay the ACS data. However, participation in differential crime types did not explain much of the gender gap in illegal pay in the DDMS. This is perhaps not surprising given our within crime type approach, as the gender gap in legal pay tends to be less pronounced within occupations (Groshen

1991). Males and females in our study reported a different rank order of the most lucrative crime type, yet across all four crimes types of inquiry, females consistently reported lower pay (see Table 7). Of course there is considerable variation in the types of activities and roles within each of the crime types. For example, the target of burglaries or the types and quantities of drugs sold greatly vary. Unfortunately, the DDMS did not contain information on the types of criminal events that respondents engaged in or the roles each played.

Psychosocial factors helped explain 26 percent of the gender gap in illegal pay, which like criminal capital, suggests that psychosocial factors are influential in illegal markets. Males have higher risk preferences than females and thus are more willing to take on risky but lucrative opportunities. While males reported being more risk taking than females in the DDMS, risk preferences did not account for much of the gender gap in illegal pay. Males also reported being more planful compared to their female counterparts. Interestingly, planfulness resulted in higher illegal pay per crime for men but not women in our sample. It is possible that males are more likely to be in positions where planning is possible and beneficial. For example, males reported higher pay for a typical burglary and forgery/fraud compared to a typical robbery whereas for females, robbery was the most lucrative crime type. Arguably, burglary and forgery/fraud are offenses that require more planning, and the rewards from such offenses are likely a function of planning. Of course, drug addiction, which is more of a problem for justice-involved women than men, will clearly affect offenders' abilities to plan their activities beyond rudimentary considerations. It also likely will affect the pay they are willing to accept for a typical crime. Our results suggest that the study of criminal behavior should explore the role of planning in criminal endeavors, an understudied construct in the criminal realm.

When comparing the DDMS community sample to the DDMS incarcerated subsamples ("earners" and "non-earners"), we found more pronounced differences between females in the community sample and females in the incarcerated sample than their male counterparts. However, in the incarcerated sample, the difference between female "earners" and female "non-earners" was less pronounced than among males. One potential explanation is that incarcerated females may be a more homogenous group than incarcerated males. As Worrall (1990) described, incarcerated women tend to be more disadvantaged than their male counterparts. As a group, they are also much more apt to be incarcerated for drug crimes than men (Mauer 2013). This fact, coupled with the higher levels of stigma for female criminals (as counter-type) may explain some of our findings. The homogeneity and disadvantage also bears out in a pay gap in the illegal market. Incarcerated females were more likely to believe they could earn more illegally than legally and reported lower illegal reservation prices, the lowest amount of pay they will accept to engage in a particular crime, than male offenders (see "Appendix B"). That is, female offenders reported a willingness to accept *less* pay than their male counterparts for the same crime type. In contrast, as compared to male DDMS community members, female DDMS community members reported more of a tendency towards expecting to earn the same illegally as legally and higher illegal reservation prices.

Reservation prices (legal and illegal) are especially useful when considering policy implications. Prospect theory (Kahneman and Tversky 1979) suggests that differences in reservation wages between males and females can partially be accounted for by earnings expectations, perceived labor market discrimination and prior salaries (Goldsmith et al. 2004; Orazem et al. 2003). Lower legal reservation wages could serve as comparisons to what females are willing to accept in the illegal market, and prior experiences with illegal pay or knowledge of illegal pay among other females may serve as anchors in the illegal markets, resulting in lowered illegal reservation prices and subsequent illegal pay. Thus, if women turn to crime, structural conditions and financial need may drive females to expect and be willing to accept less for engaging in crime. The likely result then is that women make less for engaging in the same types of crime as men, which our findings support.

Data from the ACS speculatively supports the notion that there are earning disparities in legal pay across gender, even when accounting for age, education, race/ethnicity, average hours worked, industry, and secondary/entry level jobs. The gender pay gap in both the legal and illegal markets in Delaware at approximately the same time period suggests that policy makers may look to incentives in the legal labor market to draw women away from the illegal market compared to males, who make more in the illegal market. Similarly, gendered responses to reducing barriers to entry in the legal labor market may be especially salient given the pay disparity in the illegal market. For example, women are often the primary caretaker of their minor children (Greenfeld and Snell 1999), and thus incentives such as flexible work schedules and opportunities for child care could be important elements for hastening the desistance process.

Unexpectedly, race accounted for a large portion of gender gap in illegal pay per crime. Unlike research on the legal labor market, we observed a large illegal pay *premium* for non-whites among both males and females. While unequal entry into the illegal market by race as a consequence of limited legal economic opportunities has been well established (e.g. Crutchfield and Pitchford 1997; Edelman et al. 2006; Sullivan 1989), less clear is why non-whites earn higher illegal pay compared to whites. Ethnographic work reveals that many young men that face restricted legal job market opportunities look to crime as a way of "getting paid" (Sullivan 1989) and that "the pattern of one's employment or lack of employment influences the degree to one's criminal involvement" (Crutchfield and Pitchford 1997:93). It is possible that weakened bonds to legal markets is associated with a stronger commitment to the criminal world, resulting in higher rewards to crime. Relatedly, opportunities in the illegal market are heavily, if not entirely, reliant on informal social connections. Criminal social capital is hypothesized to provide more lucrative opportunities and has been shown to be positively associated with illegal earnings (Loughran et al. 2013a, b; McCarthy and Hagan 2001). One avenue of exploration is the differences in criminal social capital between non-whites and whites. Given the strong relationship between monetary rewards and persistence in offending (Pezzin 1995; Shover and Thompson 1992), future work could focus on the dynamics between race, legal labor markets and criminal success.

Limitations and Future Directions

Our quantitative approach is among the first of its kind and complements existing qualitative research. We provide preliminary insight into the gender gap in illegal pay; however, future research should build and improve upon our study in a number of ways. First, we were only able to measure illegal pay per crime for four crime types—robbery, burglary, drug selling and forgery/fraud—but found "within occupation" gaps (i.e., pay gaps within crime types) across the four types measured. Being able to examine a broad array of crime types, including less serious crimes such as sex work, shoplifting, theft, or fencing, would be informative on the nature of the gender gap in illegal pay. Similarly, we were not able to determine the extent to which gender differences in pay might be a function of predicate circumstances or offenses.

A second limitation of our study is that we were not able to ascertain if the subjects tend to offend alone or in a group, and if they generally tended to offend in a group, their role within the group. On one hand, the literature on group offending suggests that females are more likely to participate in group offenses compared to males (Van Mastrigt and Farrington 2009). Additionally, research shows that same gender dyads are more common than mixed (Carrington 2016) and that women take on a variety of roles in illegal markets (e.g., Deitzer et al. 2019). One possible explanation that we were not able to explore is that women more often share profits with their accomplices. For example, in a study using the NIBRS data, co-offending incidents were associated with greater total property value stolen but co-offending incidents resulted in significantly less property value per offender when assuming profits are split evenly (Tillyer and Tillyer 2015), which may not be the case (see Steffensmeier and Terry 1986). Although "property value" is not a perfect analog to illegal pay, it suggests that individuals involved in group crime gain less personally. On the other hand, a study conducted to specifically examine the relationship between co-offending and illegal returns to crime found that co-offending was associated with the probability of *receiving any* illegal income but not variation in illegal income (Rowan et al. 2018), the focus of the current study.

Third, although there is a rich qualitative literature on the nuances of women's offending and the ways in which gendered differences in addiction and parenthood may affect the choice of offending and pricing, we do not have direct measures of these contextual factors. Similarly, we cannot unpack the ways in which offending opportunities may be nested (e.g., sex work and robbery), which also may affect the gender gap in illegal pay.

Lastly, other metrics of illegal pay and samples should be utilized to further examine the gender gap in illegal pay. The metric of illegal pay used in the current study was a "typical crime," which perhaps provides the best comparable unit of measurement to a legal wage. Crime is volatile and pay for some months or even weeks can differ considerably. Moreover, frequency of offending is often conflated with time aggregated measures of illegal earnings, exacerbating measurement error. For example, males tend to offend more frequently than females (Farrington and Painter 2004); thus, the unadjusted gap will likely be more pronounced in aggregate estimates. It is likely that a "typical" crime produces lower bound estimates of the gender gap in illegal pay making our estimates of the gender gap conservative. Additionally, the DDMS may be specific and unique to incarcerated populations in Delaware and caution against any generalizations of the results. The illicit market structures from which offenders are drawn may be unique to place. We therefore encourage future research to collect and analyze data from different locations and places.

In sum, we found that indicators of the gender gap in legal pay can be translated to criminal contexts to help uncover potential correlates of illegal pay differentials. The findings of this study complement qualitative accounts to provide preliminary quantitative evidence that females likely face real disadvantage in the criminal world. Given the importance of rewards in offender decision making and the desistance process, we urge scholars to examine differential reward structures by analyzing and collecting data from a variety of sources and samples. Understanding these structures better could provide useful information for shifting women at the margins from criminality to the legitimate job sector as well as when and with whom to time such interventions.

Appendix A: Gender Gap in Illegal Pay in Other Data Sources

See Fig. 1 and Table 6.

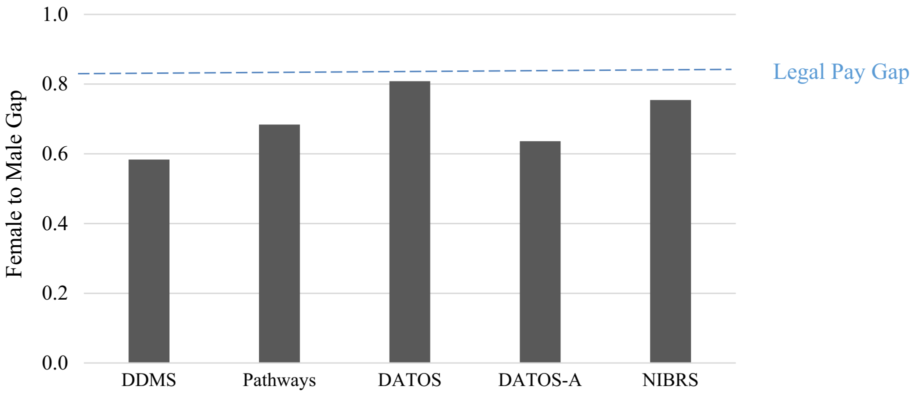

Fig. 1 Average female to male ratio, unadjusted

Table 6 Description of data sources

	Time	Sample	Sample size	Time aggregation
Delaware decision making study	2016	Incarcerated offenders adults 18 +	F = 123 Offenses; 65 people M = 506 Offenses; 279 People	Typical offense
Pathways to desistance	2001–2010 Ages 14–26	Serious young offenders	F = 78 Obs; 38 People M = 1,193 Months; 524 People	Per offense
Drug abuse treatment outcomes (DATOS)	1991–1994	Adults in drug treatment adults 18 +	F = 234 M = 1,595	Per offense
Drug abuse treatment outcomes—adolescents (DATOS—A)	1993–1995	Adolescents in Drug Treatment	F = 638 M = 1,240	Per offense
National incident-based reporting system (NIBRS)	2016	Incidents known to police adults 18 +	F = 327, 265 Incidents M = 701, 254 Incidents	Incident solo-offenses only

Appendix B: Descriptive Statistics by Crime Type and Gender

See Table 7.

Table 7 Descriptive statistics of incarcerated sample by crime type

	Robbery		Burglary		Drug dealing		Forgery	
	Males	Females	Males	Females	Males	Females	Males	Females
	n = 136	n = 34	n = 130	n = 23	n = 253	n = 66	n = 69	n = 34
Earnings								
Illegal Pay (log dollars)a	7.10 (2.24)	6.36 (1.63)	7.04 (2.02)	6.68 (1.68)	6.98 (2.14)	6.54 (1.83)	6.90 (2.12)	6.52 (1.70)
Illegal Reservation Price (log dollars)	7.98 (3.21)	7.87 (3.85)	8.43 (3.54)	7.59 (3.78)	8.95 (3.53)	7.95 (3.42)	8.51 (3.72)	7.62 (3.43)
Earnings Expectations	2.12 (0.87)	2.50 (0.82)	2.13 (0.87)	2.52 (0.78)	2.24 (0.85)	2.39 (0.83)	2.00 (0.90)	2.53 (0.74)
Demographics								
Age	32.16 (9.40)	33.88 (8.98)	33.40 (9.90)	32.70 (9.12)	31.79 (9.17)	32.19 (9.15)	34.44 (9.20)	34.00 (8.58)
White	0.39 (–)	0.74 (–)	0.60 (–)	0.87 (–)	0.45 (–)	0.64 (–)	0.54 (–)	0.71 (–)
Black	0.51 (–)	0.24 (–)	0.33 (–)	0.13 (–)	0.50 (–)	0.31 (–)	0.39 (–)	0.26 (–)
Hispanic or Other	0.10 (–)	0.03 (–)	0.07 (–)	0.00 (–)	0.10 (–)	0.04 (–)	0.07 (–)	0.03 (–)
Criminal capital								
Age First Crime	13.21 (3.32)	16.76 (6.51)	14.06 (4.74)	16.57 (5.30)	14.25 (4.22)	16.31 (5.25)	14.83 (5.08)	17.78 (5.93)
Number of Arrests	8.63 (7.59)	8.91 (7.83)	8.88 (7.71)	8.09 (7.24)	7.22 (6.57)	7.25 (6.26)	10.26 (7.91)	6.89 (4.76)
Specialization	2.61 (0.84)	2.71 (0.90)	2.63 (0.85)	2.74 (1.12)	1.99 (0.96)	1.99 (0.99)	2.72 (0.93)	2.41 (1.04)
Psychosocial attributes								
Risk Preferences	0.24 (1.03)	− 0.02 (0.87)	0.25 (1.04)	0.02 (0.89)	0.22 (1.09)	− 0.00 (0.82)	0.29 (1.03)	− 0.09 (0.83)
Impulsivity	3.73 (0.73)	3.64 (0.84)	3.75 (0.75)	3.60 (0.77)	3.71 (0.70)	3.70 (0.72)	3.75 (0.65)	3.56 (0.68)
Planfulness	3.33 (1.05)	3.15 (0.63)	3.32 (0.71)	3.15 (0.68)	3.41 (0.91)	3.13 (0.72)	3.24 (9.21)	3.16 (0.73)

[a]For individuals who reported illegal pay

Appendix C: Probability of Income Generating Crime

See Table 8.

Table 8 Linear probability models predicting probability of income-generating crime

	Males (n = 395 ppl)		Females (n = 116 ppl)	
	B	SE	B	SE
A. Race/Ethnicity				
Black vs. White	0.05	0.05	– 0.05	0.10
Hispanic and Other vs. White	0.13	0.08	– 0.24	0.26
B. Criminal capital				
Age First Crime	– 0.02***	0.00	0.01	0.01
Number of Arrests	0.01**	0.00	0.01†	0.01
D. Psychosocial attributes				
Risk Preferences	0.02	0.21	0.04	0.06
Impulsivity	0.10**	0.03	0.15*	0.07
Planfulness	0.01	0.03	– 0.04	0.06
Constant	0.07	0.18	– 0.39	0.41

† $p < .10$ * $p < .05$ ** $p < .01$ *** $p < .001$

Appendix D: Sample Selection

We address the problem of sample selectivity bias in estimating illegal pay by using the Heckman (1979) two-equation model where selection can be treated as a form of omitted variable bias.

We use multiple exclusion restrictions (i.e., variables that are theoretically important to explain selection into income-generating crimes, but do not explain the amount of illegal pay). Under the null hypothesis H_0: $\rho = 0$ selection is exogenous and Eqs. 2 and 3 can be consistently estimated using OLS. Rejection of H_0 implies a selection problem. We use these corrected estimates in the decomposition model.

Exclusion Restrictions

Earnings Expectations: Because incarcerated persons do not have current legal wage offers, we are interested in their subjective expectations of potential legal earnings relative to potential illegal earnings upon release. Expecting to make more illegally than legally will result in a higher likelihood of selecting into income-generating crimes. When women perceive gender discrimination, they lower their earnings expectations (Orazem et al. 2003), which in turn could lead to lower pay and subsequent wage growth. Earnings expectations are asked of all respondents: "How much money do you think you could make illegally compared to a legal job?" Reponses are categorical: 1 = more legally, 2 = about the same and 3 = more illegally. Within the incarcerated sample, on average earners expect to make more illegally than legally than non-earners. This holds across gender, yet females tend to have a greater tendency to expect to earn more illegally than legally than males.

Illegal Reservation Price: This measure is directly analogous to the legal reservation wage. Reservation wages encapsulates all of the relevant information in an individual's job search behavior and can depend on a number of individual factors such as gender (Killingsworth and Heckman 1986), race and ethnicity (Freeman and Holzer 1986; Holzer 1986), or degree of risk aversion (Devine and Kiefer 1991; Pannenberg 2007). Just like the legal sector, motherhood theoretically factors into the illegal reservation wage such that females who have children are less likely to engage in offending (Kreager et al. 2010; Yule et al. 2015). Conversely, local life circumstances, such as addiction to illicit substances can theoretically lower an individual's illegal reservation price given that addiction fuels the need for quick cash (Uggen and Thompson 2003). The higher the illegal reservation price, the less likely an individual will engage in the crime for pay. Illegal reservation price is asked for each of the four crime types (drug selling, burglary, robbery, or forgery): "What is the lowest amount of money you would need to earn to participate in [crime type]?" The measure was skewed, so we top-coded to a million dollars and then logged.

We account for selection into the four crime types we analyze with several exclusions restrictions. With valid exclusion restrictions, the Heckman method generally performs comparably or significantly better than OLS (Lennox et al. 2012; Puhani 2000). However, in the case of weak exclusion restrictions or multicollinearity, the Heckman method can produce biased estimates and can be less efficient than OLS. Overall, we observe that the Heckit estimates are substantively similar to the OLS estimates, suggesting that selecting into income-generating crimes among the incarcerated sample does not produce substantial bias.

See Tables 9, 10.

Table 9 Ordinary least squares regression models predicting illegal pay (log) with Heckit

	Males (n = 506 obs; 279 ppl)				Females (n = 123 obs; 65ppl)			
	OLS		Heckit		OLS		Heckit	
	B	Robust SE	B	SE	B	Robust SE	B	SE
A. Race/Ethnicity								
Black vs. White	0.97***	0.21	0.95***	0.21	0.92*	0.46	0.87*	0.43
Hispanic and Other vs. White	0.98**	0.32	0.95**	0.32	− 0.12	1.15	0.09	1.10
B. Criminal capital								
Age First Crime	− 0.01	0.02	− 0.00	0.02	− 0.10**	0.04	− 0.10**	0.03
Number of Arrests	0.00	0.01	− 0.01	0.01	− 0.02	0.03	− 0.03	0.03
Specialization	0.01	0.10	0.05	0.10	− 0.09	0.18	− 0.06	0.17
C. Crime types								
Burglary vs. Robbery	0.25	0.28	0.26	0.28	− 0.24	0.57	− 0.19	0.54
Drug Selling vs. Robbery	− 0.66*	0.25	− 0.53*	0.25	− 0.89†	0.48	− 0.82†	0.45
Forgery vs. Robbery	0.57†	0.36	0.61†	0.35	− 0.66	0.53	− 0.60	0.50
D. Psychosocial attributes								
Risk Preferences	− 0.08	0.09	− 0.03	0.09	0.25	0.22	0.26	0.21
Impulsivity	0.06	0.14	0.08	0.14	− 0.24	0.28	− 0.29	0.27
Planfulness	0.38**	0.13	0.39**	0.13	0.31	0.25	0.27	0.24
Constant	5.34***	0.91	4.60***	0.94	8.83***	1.88	8.25***	1.83
Exclusion restrictions								
Illegal reservation price			− 0.19***	0.01			− 0.17***	0.02
Earnings expectations			0.00	0.04			0.31**	0.09
Rho			0.28	0.10			0.27	0.19

† $p<.10$ * $p<.05$ ** $p<.01$ *** $p<.001$

Table 10 Decomposition models of the illegal gender pay gap with Heckit (n = 629; 344 ppl)

	OLS		Heckman Correction	
Variables	Log Points	Exp(b)	Log Points	Exp(b)
Panel A				
Males	7.05	$1156	6.57	$715
Females	6.51	$675	6.08	$438
Total Pay Gap	0.54	1.71	0.49	1.63
Endowments	0.60	1.83	0.59	1.81
Coefficients	0.23	1.26	0.19	1.21
Interaction	− 0.30	0.74	− 0.30	0.74
Panel B				
A. Race/Ethnicity	0.23	1.26	0.23	1.26
B. Criminal Capital	0.09	1.10	0.09	1.10
C. Crime Types	− 0.03	0.97	− 0.03	0.97
D. Psychosocial Attributes	0.10	1.11	0.10	1.11
Total Explained	0.39	1.48	0.39	1.48
Total Unexplained	0.14	1.15	0.10	1.10
Total Pay Gap	0.54	1.71	0.49	1.63

Appendix E: Race/Ethnicity

See Table 11.

Table 11 Male versus female by race, unadjusted

	Black (n = 228 obs; 139 ppl)		White (n = 343 obs; 170 ppl)	
	Log Points	Exp(B)	Log Points	Exp(B)
Male	7.58	1963.13	6.52	681.17
Female	7.15	1280.47	6.32	556.44
	0.43	1.53	0.20	1.22

The gender gap in illegal pay is prevalent for both blacks and whites. Black males have the largest illegal pay premium, with an unadjusted pay of $1,963. Black females have the second highest illegal pay with $1,280 per typical crime. The unadjusted pay gap suggests that black males report 1.53 times higher pay than black females. White males report 1.22 times higher illegal pay, making an average of $681 per typical crime whereas white females report making $556 per typical crime. The race gap appears to be larger than the gender gap; black males report making 2.89 times higher illegal pay than white males and black females report making 2.29 time more than white females. Unfortunately, due to a lack of sufficient cases for females, we are not able to decompose the gender gap in illegal pay stratified by race but discuss avenues for future inquiry in the discussion section.

Appendix F: American Community Survey

Measures

Legal Pay: Our measure of legal pay is wages or salary income over the past 12 months. The weekly wage was calculated by dividing the self-reported income over the past 12 months by 51 weeks, using respondents who reported working 50–52 weeks in the last 12 months. Males ($900) earn more than females ($687) on average.

Demographics: *Age* is measured continuously. Respondents are 45 years of age on average. *Education* is recorded in categories with higher values denoting more education.[15] We treat this measure as continuous and note that women are slightly more educated than men. *Race/Ethnicity:* Categories include white alone (76%), black or African American alone (16%), and other (7%), with the racial/ethnic breakdown being fairly similar across genders.

Average Hours/Week Worked: To control for potential differences between genders in the number of hours working over the past 12 months, we control for usual hours worked

[15] 1 = no schooling completed; 2 = nursery school, preschool; 3 = kindergarten; 4 = grade 1; 5 = grade 2; 6 = grade 3; 7 = grade 4; 8 = grade 5; 9 = grade 6; 10 = grade 7; 11 = grade 8; 12 = grade 9; 13 = grade 10; 14 = grade 11; 15 = grade; 12 (no diploma); 16 = high school diploma; 17 = GED or alternative credential; 18 = some college, but less than 1 year; 19 = 1 or more years of college credit, no degree; 20 = associate's degree; 21 = bachelor's degree; 22 = master's degree; 23 = professional degree beyond a bachelor's degree; 24 = doctoral degree.

per week over the past 12 months. On average, males (41 h) work more hours per week than females (37 h).

Industry: To account for the possibility that industry may account for part of the gender gap in legal pay, we categorize industries based on IND codes.[16] In particular, we focus on five key industries: construction, manufacturing, retail trade, transportation and warehousing, and other services. While men and women in our analytic sample are fairly evenly involved in retail trade, transportation and warehousing, and other services industries, men are more involved in construction and manufacturing than women.

Occupation: Even within industries, men and women may be employed in differing occupations with differing wage distributions. To account for differences in the types of jobs in which individuals are employed, we classify occupations as secondary/entry level or not based on OCC codes.[17] Based on our classification scheme, more men are employed in secondary/entry level occupations than women (Table 12).

See Table 13.

[16] Agriculture, Forestry, Fishing and Hunting (codes 0170–0290); Mining (codes 0370–0490); Construction (code 0770); Manufacturing (codes 1070–3990); Wholesale Trade (codes 4070–4590); Retail Trade (codes 4670–5790); Transportation and Warehousing (codes 6070–6390); Utilities (codes 0570–0690); Information and Communications (codes 6470–6780); Finance, Insurance, Real Estate, and Rental and Leasing (codes 6870–7190);

Professional, Scientific, Management, Administrative, and Waste Management (codes 7270–7790); Educational, Health and Social Services (codes 7860–8470); Arts, Entertainment, Recreation, Accommodations, and Food Services (codes 8560–8690); Other Services (Except Public Administration; codes 8770–9290); Public Administration (codes 9370–9590); Armed Forces (codes 9670–9870).

[17] Management, Professional and Related Occupations are all classified as not secondary/entry level (i.e., Management Occupations; Business Operations Specialists; Financial Specialists; Computer and Mathematical Occupations; Architecture and Engineering Occupations; Life, Physical, and Social Science Occupations; Community and Social Service Occupations; Education, Training, and Library Occupations; Arts, Design, Entertainment, Sports, and Media Occupations; Healthcare Practitioners and Technical Occupations—codes 10–3540); Service Occupations are mixed classified (Healthcare Support Occupations are all classified as not secondary/entry level—codes 3600–3655; Protective Service Occupations are all classified as not secondary/entry level – codes 3700–3955; Food Preparation and Serving Occupations are mixed classified—codes 4000–4010 = not secondary/entry level and codes 4020–4150 = secondary/entry level; Building and Grounds Cleaning and Maintenance are mixed classified—codes 4200–4210 = not secondary/entry level and codes 4220–4250 = secondary/entry level; Personal Care and Service Occupations are mixed classified—codes 4300–4340, 4410, 4460–4465, 4600–4610, 4640 = not secondary/entry level and codes 4350–4400, 4420–4430, 4500–4540, 4620, 4650 = secondary/entry level); Sales and Office Occupations are mixed classified (Sales Occupations are mixed classified—codes 4700–4710, 4740, 4800–4940, 4965 = not secondary/entry level and codes 4720, 4750–4760, 4950 = secondary/entry level; Office and Administrative Support Occupations are mixed classified—codes 5000–5260, 5310–5610, 5630–5940 = not secondary/entry level and codes 5300, 5620 = secondary/entry level; Farming, Fishing and Forestry Occupations are mixed classified—codes 6005–6040 = not secondary/entry level and codes 6050–6130 = secondary/entry level); Construction, Extraction and Maintenance Occupations are mixed classified (Construction Trades are mixed classified—codes 6200, 6300–6320, 6660, 6740 = not secondary/entry level and codes 6210–6260, 6330–6600, 6700–6730, 6765 = secondary/entry level; Extraction Workers are mixed classified—codes 6800–6840 = not secondary/entry level and codes 6940 = secondary/entry level; Installation, Maintenance, and Repair Workers are mixed classified—codes 7000 = not secondary/entry level and codes 7010–7630 = secondary/entry level); Production, Transportation and Material Moving Occupations are mixed classified (Production Occupations are mixed classified—codes 7700, 7800, 7850, 7900–8200, 8220–8255, 8320, 8340, 8400–8420, 8500, 8530–8540, 8600–8640, 8720–8800, 8830–8860, 8930, 8965 = not secondary/entry level and codes 7710–7750, 7810–7840, 7855, 8210, 8265–8310, 8330, 8350, 8450–8460, 8510, 8550, 8650–8710, 8810, 8910–8920, 8940–8950 = secondary/entry level; Transportation and Material Moving Occupations are mixed classified—codes 9000–9600, 9650–9750 = not secondary/entry level and codes 9610–9640 = secondary/entry level); Military Specific Occupations are all classified as not secondary/entry level (codes 9800–9830).

Table 12 American community survey—descriptive statistics

	Full Sample (n = 16,335)		Males (n = 8,296)		Females (n = 8,039)	
	Mean	SD	Mean	SD	Mean	SD
Weekly Wages (log)	6.67	0.85	6.8	0.84	6.53	0.83
Age	44.97	13.59	44.81	13.63	45.13	13.55
Education	18.75	3.11	18.52	3.33	18.98	2.85
Race/Ethnicity						
White	0.76	–	0.78	–	0.75	–
Black	0.16	–	0.14	–	0.18	–
Other	0.07	–	0.08	–	0.06	–
Avg Hours/Week (log)	3.67	0.35	3.71	0.31	3.6	0.37
Industry						
Construction	0.06	–	0.1	–	0.01	–
Manufacturing	0.09	–	0.12	–	0.06	–
Retail	0.11	–	0.11	–	0.11	–
Transportation/Warehouse	0.1	–	0.10	–	0.09	–
Services	0.05	–	0.04	–	0.05	–
Occupation						
Secondary/Entry Level	0.28	–	0.34	–	0.22	–

$^{\dagger}p < .10$ $^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

Table 13 Ordinary least squares regression models predicting weekly legal pay (log), American community survey

	Full Sample (n = 16,335)		Males (n = 8,296)		Females (n = 8,039)	
	Mean	SD	Mean	SD	Mean	SD
Weekly Wages (log)	6.67	0.85	6.8	0.84	6.53	0.83
Age	44.97	13.59	44.81	13.63	45.13	13.55
Education	18.75	3.11	18.52	3.33	18.98	2.85
Race/Ethnicity						
White	0.76	–	0.78	–	0.75	–
Black	0.16	–	0.14	–	0.18	–
Other	0.07	–	0.08	–	0.06	–
Avg Hours/Week (log)	3.67	0.35	3.71	0.31	3.6	0.37
Industry						
Construction	0.06	–	0.1	–	0.01	–
Manufacturing	0.09	–	0.12	–	0.06	–
Retail	0.11	–	0.11	–	0.11	–
Transportation/Warehouse	0.1	–	0.10	–	0.09	–
Services	0.05	–	0.04	–	0.05	–
Occupation						
Secondary/Entry Level	0.28	–	0.34	–	0.22	–

$^{\dagger}p < .10$ $^{*}p < .05$ $^{**}p < .01$ $^{***}p < .001$

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