INSTITUTT FOR FORETAKSØKONOMI
DEPARTMENT OF BUSINESS AND MANAGEMENT SCIENCE

FOR 25 2014
ISSN: 1500-4066
June 2014

Discussion paper

A Partner in Crime: Assortative Matching and Bias in the Crime Market

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June 2, 2014

Abstract

I identify a discriminatory bias in partnership formation within the property crime market in the United States. Theoretically, the prisoner's dilemma creates an incentive for a criminal to form a partnership with a counterpart with the same probability of success, resulting in an equilibrium pattern of positive assortative matching. Using individual matched report-arrest data from the National Incident Based Reporting System and a novel empirical strategy, I pinpoint matches where the underlying probability of success of two partners differ. This difference in probability is correlated with observable characteristics, which could be evidence for discrimination and search frictions. I find patterns consistent with discrimination in male-female partnerships and patterns consistent with search frictions in black-white matches. In particular, females in a male-female partnership are more likely to evade law-enforcement than males, even though on average males are more successful as a group. This results is robust to controlling for the criminal earnings, individual criminal offenses and market characteristics. Furthermore, these patterns are found also in criminal groups of a size bigger than 2. The result could be either due to pre-crime marital matching or discrimination.

Keywords: Organized Crime, Assortative Matching, Discrimination
JEL Codes: K42, J16, J71, C78

1 Introduction

It is a well known fact that females on average earn less than males. In OECD countries, for the year 2010, females earned 77 percent of what males did. The flip side of this fact is that for the same wage, females have higher levels of observable human capital than males. If the gender wage gap is at least in part attributable to discrimination, then this bias should be found in all labour markets, especially those that face very little regulation, like the market for criminals. Generally, the gap has been attributed to a mix of three factors: first, females could be less productive than males. Second, search frictions could lead to inefficient matching and, third, discrimination. The identification of whether the gender wage gap results from discriminatory bias has been challenged by lack of good data on each side of the employer-employee match. Yet, matches in the crime market yield an additional individual outcome - which perpetrator

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got arrested. Thus, if discrimination is a pervasive social phenomenon, and if it can be found in the market for criminals, then new data can solve the identification problem of discrimination and shed a light on its effect in the market for workers.

This paper is the first to link the literature on assortative matching with that on crime and discrimination. Until now the economic literature on crime has focused on single offenders (Becker, 1968) and big organized groups. This paper is also the first to consider the building of a small group, applying the theory of assortative matching to small criminal enterprises. While discrimination in the presence of assortative matching has been explored in the context of employer-employee matches (see for e.g. Bartolucci, 2014), it has remained understudied in other matching markets with incentives for positive assortative mating.

In this paper I analyze the market for criminal partners through the lens of assortative matching. When a criminal chooses a partner with whom to commit a crime, he knows that in order to avoid a, literal, prisoner's dilemma he has to pick a counterpart who would be able to evade law-enforcement. When each criminal wants a partner with high ability of not getting arrested, this results in an equilibrium outcome of positive assortative matching, where partners have similar probabilities to evade the police (Becker, 1973). Positive assortative matching means that the probability of success between two partners are positively correlated. In equilibrium one can observe matches between two criminals with high probability of success and between criminals with low probability of success, but no matches where one partner has a high probability of success and the other has a low probability of success.

Given endogenous positive assortative matching, the difference in unobservable criminal productivity between the two partners would be zero. As this difference is zero, it should not be correlated to differences in observed characteristics. If differences in arrest outcomes (where arrest is a measure for criminal productivity) are correlated with differences in observables, then this indicates either the presence of discriminatory bias or search frictions. That is, the prisoner's dilemma incentive sets the counterfactual difference in productivity to zero, thus any observed difference could be attributed to frictions or bias[1]. To clarify the empirical intuition consider the following example: in a frictionless market, if a male indulges a discriminatory bias towards females, he would require a skill premium to match with her and she would match with him if she has a positive bias for males. Thus, he would match up and he would be compensated for his bias with the difference in probability of success. Once the crime is commited, it is likely that he will get arrested and she not, thus the difference in observed probability of success would be correlated to the source of bias - gender. Additionally, in biased matches the difference in productivity is different from zero.

However, if the environment is not frictionless, the difference in criminal productivity between the two partners would not be zero. Then, in the extreme case partners would match randomly with the first arriving candidate and the difference in productivity between them would be equal to the difference in average productivity between the two demographic groups whose members form a partnership.

Empirically, if only one partner gets arrested, then there could be a productivity difference between the partners. If this success difference turns out to be systematically correlated with observables, then there is a bias or frictions in matching. The only way to distinguish between biased matching and frictions is by taking into account the average probability of success of the demographic groups, whose members commit to a partnership. Whenever the difference in criminal ability between partners has an opposite sign to the difference induced by random matching, then this would be evidence of discriminatory bias.

For the purpose of identifying a bias I use over one million individual observations on criminal partnerships in property crime from the National Incident Based Reporting System (NIBRS) in the period 1995-2011. By matching crime reports to arrests, I define the probability of success as

[1] One can think of discrimination as a bargaining friction, but in this paper it will be considered separate from all other frictions.

the probability of not being arrested. This probability reveals information about the criminal's law-evasion skills, namely whether the criminal is good at evading the police or not. This measure already discounts information from preferential treatment from the police for a certain demographic group, if such treatment exists (see for e.g. Persico & Todd, 2006) and it is a relevant measure of productivity about which criminals care. Only the outcome is observed by the econometrician, while the real probability may be observed by the partner in crime.

By modeling criminal partnerships in this way, I find that in black-white partnership, white criminals turn out to face a lower probability of success unconditionally and conditionally, both as a demographic group and as partners of successful blacks. These differences in probability are consistent both with bias and search frictions. When considering gender, unconditionally males are more successful than females. However, in male-female partnerships the females are more successful than the males. Therefore, females match with less productive males. Equivalently, from the perspective of the males, they match with females with higher probability of success than their own. This pattern could be due to search frictions but it is more consistent with a discriminatory bias.

The bias in male-female matches could have different sources. From all probable sources of bias, several can be rejected right away. First, females might be assigned the safer role in the commission of the crime because of gender stereotypes, and thus they have a higher success probability conditional on the match. In a robustness check I show evidence that the bias still holds when accounting for the type of crime commited. Second, if there is an unfavourable sex-ratio so that the underrepresented group could have a bargaining advantage (like when marrying up, see for example Becker, 1973; Abramitzky *et al.*, 2011). However, matches in the criminal market are not constrained to consist of a male and female (unlike in the traditional marriage market), therefore, matching should not be influenced by the sex ratio. Furthermore, in a robustness check I take subsamples of criminal markets with different sex and race ratios and the results remain robust. Third, reporting biases related to crimes could be creating spurious correlations. However, when I control for measurement errors by taking a subsample with only arrested couples and a subsample of daylight crimes, results remain robust. Fourth, controlling for the monetary value of the property stolen and taking into account gang membership does not change the results. Finally, in a falsification exercise on criminal groups of three I show that the same result holds.

There are two explanations, alternative to discriminatory bias, for the result I obtain. First, the bias could be due to reputation, where females have a worse reputation than males, so that they have to compensate for it with higher criminal ability. This is consistent with an early suggestion by Steffensmeier (1980), who notes that males are less likely to choose to commit a crime with a female because females are deemed to be governed by passions and, thus, they are not trustworthy. Second, arrest differences could be the consequence of pre-crime matching. Male-female matches are more likely to be the result of marriage market matches, where male scarcity can lead females to date down and this would be apparent in the criminal market. A caveat of this explanation is that several studies find that marriage partners in the US increasingly match assortatively with respect to earnings, academic achievement and intelligence (see for e.g. Bredemeier & Juessen, 2013).

This empirical test could be applied to a diverse set of matching markets if there were no data limitation. For example, academic co-authorships are also formed along the incentive to pair up with a partner, who is better at publishing articles, generating a similar pattern of positive assortative matching. However, in that setting only the match specific outcome of publishing is known and not the individual productivity. While the underlying populations in academia and crime differ in many characteristics, if this type of gender discrimination is pervasive across spheres of society, it implies that females in male-female co-authorships could be more productive than males. This test cannot be applied to marital mating, despite the similar matching incentive, because these matches are constrained to consist of a male and female, thus the quest for gender bias is superfluous. The preference for own race has already been documented in online dating by Hitsch *et al.* (2010) and caste (as a similar salient categorical characteristic) by Banerjee *et al.* (2013). Similarly, this test cannot be applied to the labour market because productivity differences between the employer and employee are not zero, for example due to hierarchy and experience. Yet, if discrimination is a social condition, finding evidence of it in the unregulated crime markets points to its existence in other spheres of society, among which the named academic and labour ones.

Considering implication for law-enforcement, it is notable that I find evidence of persistent search frictions in matching between whites and blacks. If this can be traced back to taste discriminating bias, this means that one can hinder the exchange of criminal capital between prison cell-mates if they are of different race. However, whether this is ultimately the case would have to be accessed by future research.

In this paper, by the virtue of arrest data, I link matching to a productivity measure, thus detecting discrimination. There are two sides to the literature on assortative matching. From the theoretical perspective, Becker (1973) has applied the concept of positive assortative matching to marital pairing in which there is positive correlation between the abilities of two spouses. Shimer & Smith (2003) introduce frictions in the matching market and define additional conditions in which assortative matching holds[2]. From the empirical side, Abramitzky *et al.* (2011) and Angrist (2002) consider the effect of sex ratios on assortative mating. Theoretically, as long as matches are constrained to consist of a male and a female, an unbalanced sex ratio endows one gender with an advantage in securing a better partner with respect to an environment with a balanced sex ratio. But a marriage is not like a criminal partnership (although individual opinions may differ). The crime market is characterized by unbalanced sex and race ratios, however, matches are not constrained in composition. Therefore, not one demographic group has explicit bargaining power and this allows me to identify a bias.

Empirically, I take the difference in the criminal skill measure of partners in order to determine the pattern of matching, rather than looking at correlations between traits, as do for example Pencavel (1998) and Rose (2007), and I take the analysis a step further into the realm of discrimination. Lang & Lehmann (2012) provide an up-to-date discussion of the literature on discrimination. Looking for evidence of frictions and discrimination in this reduced-form approach, contrasts with structural models on search in the labour market (such as Bartolucci, 2014; Flabbi, 2010). While structural assumptions relax data requirements, the crime market offers the individual specific productivity measure of arrest which allows me to pinpoint the presence of a bias intuitively.

While the notions of assortative matching and similarity in observables(preference-for-same) are used interchangeably in some contexts such as network theory, here they can be treated separately. Many studies have identified the preference for same. Bagues & Perez-Villadoniga (2012) show in a natural experiment that recruiters prefer applicants who have similar to their own set of skills. Arcand & Fafchamps (2012) demonstrate assortative matching in social traits like ethnic proximity and wealth between members in community-based organizations in developing countries. In the setting of the crime market, I can disentangle matching on productivity from matching on observables, aka discrimination.

Finally, this paper is related to the economic literature on crime. Starting with Becker (1968), research has addressed individual decision making and aggregate relationships, however, not in the context of co-offending. The latter matter is missing in the recent literature review by Levitt & Miles (2007). The criminological literature has given more attention to the organization of small crimes and Alarid *et al.* (2009) provide evidence from prison interviews that offenders choose to commit a crime with a friend (from the same social circle) resolving issues of trust by matching along social ties. Van Mastrigt & Carrington (2013) provides a review on the literature from the perspective of network homophily (similarity in observables) in group offending, noting

[2] Smith (2011) reviews this literature.

that there is an incentive to select a successful partner, however stopping short at selecting him from the local offender pool and not considering the implications of this incentive, as it is done in this paper. A further related novelty of this paper is that it finds evidence of a gender bias in the crime market. In a similar vein, Gavrilova & Campaniello (2013) find that in the crime market females earn on average the same as males do, but they face a higher likelihood of arrest, documenting a gender arrest and participation gap and opening the field for investigating discrimination in the crime market.

The structure of the paper is the following. First, in section 2, I present the data and some preliminary results. Section 3 describes a simple static matching model that will aid the intuition with the identification strategy and interpretation. In sections 4 I discuss the empirical strategy. In sections 5 and 6 I turn to results and robustness checks. Section 7 concludes.

2 Data

The source of criminal data for this paper is the National Incident Based Reporting System (NIBRS), covering criminal incidents in the United States. The sample period runs from 1995 to 2011. NIBRS consists of repeated cross-sections, where the data points are individual level records on crime incidents submitted by law enforcement agencies. These records provides details on how many perpetrators were involved in one incident, their demographic characteristics (such as age, gender and race) and the characteristics of the crime. For example an armed robbery is commited by 2 white males at a liquor store. The victim (or witnesses) would report to the police the time of the crime, how much was stolen and what the offenders look like. Both offenders would be recorded with a robbery Uniform Crime Report (UCR) code and one (or both) of them would be recorded as using a weapon. When the police arrests one of the robbers it will note in the incident file that there has been one arrest and it would link the arrest incident to the robbery incident. This example spells out the advantages of the NIBRS over other crime data. It provides individual crime reports rather than yearly totals, demographic characteristics of perpetrators, arrest outcomes for each criminal, the nature and characteristics of the crime.

The main caveat of the NIBRS data is that it is not representative for the US. In the beginning of the sample period, in 1995, 290 agencies from 9 states submitted data, while in 2011, 1908 agencies from 36 states did so. The NIBRS is representative for crimes in the jurisdictions of smaller and medium-sized agencies. Given that submitting individual crime reports is a costly activity, there are a few big agencies that submit data. In a given county there exist from 1 to 36 reporting agencies, depending on population size and historical factors. Given that one city can be overseen by several law-enforcement agencies, which could have a traditional focus on neighborhoods or types of crime, it is likely that outcomes within an agency's jurisdiction are correlated. Therefore, in the main analysis I cluster the errors on the agency variable and provide a robustness check with city clustering. Despite this caveat, it is important to note that inference in this paper is drawn on the universe of the reported property crime in the agencies that submit reports.

There are three main reasons for which I concentrate my analysis on property crimes. First, males have a natural advantage in perpetrating assault and similar crimes because of the direct contact with the victim. However, property crimes have the aim of appropriating money or property with no threat of force against the victims, therefore offending is relatively independent of diverse physical endowments between genders. Second, the property crime rate for 2011 was estimated at 2,905 crimes per 100,000 inhabitants (UCR 2012). This is roughly 7 times more that the violent crime rate. Third, the data offers the opportunity to observe over what prospect of criminal earnings did two offenders match.

According to the Uniform Crime Reports, the following crimes are defined as property ones (UCR codes in parenthesis): arson[3](200), robbery (120), burglary (220), larceny offenses such

[3]Arson is an intentional damage of property through the setting of fire. The usual motive is insurance fraud

as pocket-picking (23A), purse-snatching (23B), shoplifting (23C), theft from building[4] (23D), theft from coin operated devices[5] (23E), theft from car [6] (23F), theft of motor-vehicle parts (23G), all other larceny (23H), motor vehicle theft (240) and selling of stolen property (280).

The NIBRS data is composed of several data sets. For this study I utilize the datasets on offender reports, property crimes and arrests. I select all property crimes commited in a 2 person partnership with the following procedure: for a given year, I exclude agencies that do not submit reports for the whole year. I merge the incident reports with the property data. To the resulting dataset I merge the arrest data, using as a key the incident number, the race and gender of the offender. This allows me to analyze all the available information on a certain type of crime. When filtering the observations, dropping individuals for which all the characteristics of gender and race are unknown, leaves me with 98 percent of the initial partnership data[7]. I select prime age perpetrators between 15 and 65 years of age, which leaves 78 percent of the initial data[8]. I concentrate my analysis on black and white criminals, but I provide robustness checks with the other races in the sample.

Table 1 presents the summary statistics for criminal partners. The average criminal is 26 years old. 65 percent of all criminals are white (caucasian and hispanic), 31 percent are female. 60 percent of all criminals succeed in evading law-enforcement, or equivalently, 40 percent get arrested. Criminal markets on average are diverse and thus no demographic group holds a specific advantage in numbers. [9]. The mean criminal earnings are 1,113 USD. Offenders from Indian and Asian origin are in total 1 percent of the sample. Most offenses are observed in shoplifting, followed by all other larcenies and burglaries. In total there are 2, 174, 742 individual observations, yielding 1, 087, 371 observed partnerships over the sample period.

In Table 2 I present the cross-tabulation of pairs. The first column shows the total frequency of the 4 types: black males, black females, white males and white females. The second column denotes the success rates for each type. The remaining columns in table 2 show how often does a category of criminal, for example white male, choose a criminal in the other category. Note that black males emerge as the most successful and white females as the least successful criminals[10]. 78% of the black males pair up with other black males, followed by black females. Black females choose one another in 63% of the cases. White males choose other whites in 95% of the cases, of which 73 percentage points are other white males. White females have a similar preference for other whites, but 51% of them also choose their own gender. Cross-race matches occur on average in 8% of the cases for each type of criminal. On average, each type is observed to prefer his own type as a partner.

In Table 2 it is observed that on average criminals prefer partners of their own type. Black males form a match with other black males in 78 percent of the observed matches, white males match between themselves in 73 percent of the matches. Black and white females do so respectively in 63 percent and 51 percent of the matches. 10 percent of the black males match with black females, while 21 percent of the white males commit crimes with white females.

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or vandalism.

[4]The precise definition is: "A theft from within a building that is open to the general public and where the offender has legal access." Taken from the Uniform Crime Reporting Handbook.

[5]Theft from coin-operated devices are classified as such when, for example, a cigarette vending machine is rifled for money and/or merchandise.

[6]For example, a car is broken into and an umbrella is stolen.

[7]Selecting the couples already leaves out crimes in which the offenders were not observed.

[8]These 20 percent of dropped observation are either on young offenders, too old one or offenders whose age is unknown.

[9]The variable *diversity* denotes the average diversity of demographic characteristics of criminals within the jurisdiction of an agency. This variable is the product of the fractions of females, males, whites and blacks, normalized by the maximum the product can obtain, so that it varies between 0 and 1: Diversity$=\frac{females*males*whites*blacks}{0.5^4}$. It would attain a value of 0 if a given market is homogeneous in the type of criminals and as the heterogeneity increases so does *diversity*.

[10]This ordering holds also in individual crimes, where black males succeed in 73 percent of the crimes, white males in 63 percent, black females with 59 percent and white females with 55 percent.

Table 1: Summary Statistics

	Mean	SD	Min	Max
White	0.655	0.476	0	1
Asian	0.006	0.076	0	1
Indian	0.007	0.084	0	1
Female	0.309	0.462	0	1
Age	25.724	9.929	15	65
Success	0.593	0.491	0	1
Diversity	0.398	0.341	0	1
Earnings	1113.213	3129.035	0	86970
Arson	0.005	0.069	0	1
Pocket-picking	0.002	0.044	0	1
Purse-snatching	0.003	0.055	0	1
Shoplifting	0.278	0.448	0	1
Theft from Building	0.073	0.260	0	1
Theft from Coin-Operated Machine	0.003	0.052	0	1
Theft from Motor Vehicle	0.057	0.233	0	1
Parts	0.013	0.113	0	1
All Other Larceny	0.182	0.386	0	1
Motor Vehicle Theft	0.049	0.216	0	1
Burglary	0.153	0.360	0	1
Robbery	0.102	0.302	0	1
Stolen Property Offenses	0.017	0.130	0	1
Observations	Sample:	2 174 742	Total:	2 215 362

Notes: An observation is a criminal in a crime committed in jurisdiction of an agency in certain date and hour. The success rate is the complement to the arrest rate. Each criminal has one or more offenses on his record for the crime reported. Diversity takes a value 0 whenever in a given year-agency cell the market is restricted to only whites, only blacks, only females or only males. The total sample consists of 2 215 362 individual observations. The estimation sample excludes Asians and Indians (a robustness check is provided) and it consists of 2 174 742 individual observations.

Table 2: Cross Tabulation of Pairs

	Total	Success	Black Males	Black Females	White Males	White Females
Black Males	0.251	0.708	0.777	0.097	0.085	0.041
Black Females	0.087	0.513	0.281	0.629	0.026	0.064
White Males	0.441	0.590	0.049	0.005	0.733	0.213
White Females	0.222	0.506	0.046	0.024	0.423	0.506

Notes: An observation is a criminal partner in a crime committed in jurisdiction of an agency. The last four values for each row sum to 1.

Table 3: Tabulation of the Probabilities of Success

	Unconditional	Conditional on Own Group	Conditional on Other Group
Females	0.506	0.416	0.630
Males	0.633	0.635	0.624
Blacks	0.657	0.662	0.618
Whites	0.562	0.559	0.614

Notes: The first column of numbers denotes the unconditional probability of success of a given demographic group. The second column denotes the probability of success, conditional on forming a match with a member of the same demographic group. The third column presents the same figure, conditional on a match with a member for the other demographic group: for females it is males and vice versa, for whites it is blacks and vice versa.

Obviously, the choice for a matching partner is not random. For example, if black males were selecting partners randomly, then they would choose white males in more cases (44 percent) than the 8.5 percent they do it.

In Table 3, the difference in conditional probabilities of success is tabulated. From it, one can observe that females matching with males have a higher probability of success than the ones matching with other females. Males face conditionally and unconditionally similar probabilities across all three columns, while whites that match with blacks face a higher probability of success than whites that match with other whites. Similarly, blacks matching with whites have a lower probability of success than those that match with other blacks. Yet, matches between groups seem to be between criminals with similar probability of success.

Thus, criminals do not match randomly and they have an explicit tendency to match with a partner with the same demographic characteristics (that is, black males match with only black males). The preference for same partner could be due to three reasons. First, successful partners could be able to find other successful counterparts only in their own demographic group. This could be the case of black males, whose probability of success is highest and it is less likely to be matched by white females. This implies that criminal success is non-randomly distributed with respect to demographic groups. Yet, in table 3 one can see that whenever black form a match with whites their probabilities of success are similar (last two rows, last column). Thus, the distribution of the probability of success is at least overlapping between the different groups. Second, search frictions might preclude the matching between successful partners from different demographic group. For example residential segregation could lead to successful whites not meeting their best black counterpart and thus picking the second best from their own demographic group. Third, the preference for same partner could be due to an explicit bias against matching with a different demographic group. Thus, the figures in Table 2 could be due to any and/or a mix of these 3 reasons. The next section will add the complexity of a toy model in order to illuminate how the effect of bias could be identified among all these possible explanations.

3 Model

In this section I introduce a simple model of assortative matching, which demonstrates the analytical framework for the empirical strategy in the next section. The aim of this application of assortative matching is to arrive at a test for discrimination.

3.1 Frictionless Matching

When a suitable crime opportunity presents itself, a criminal has to choose a partner with whom to exploit it. A partner might be required for a variety of motives, for example, complementarity in skills, mentorship or courage. While motives differ in the individual case, policing technology provides a strong incentive for the type of matching. Given the practice of offering a plea bargain to the criminal partner arrested first, each criminal associate faces the incentive to pair up with the most successful possible counterpart. Considering the prospects offered by the prisoner's dilemma, in this classical setting, each criminal would prefer a partner who would not get arrested. Considering the incentive for a successful associate from both sides of the partnership, it seems straightforward that there should be positive correlation between criminal ability traits between partners, that is, positive assortative matching on probability of arrest.

Introducing the criminals, assume that there is a unit continuum of them, each indexed by a probability of success $p \in [0, 1]$. p is strictly increasing in criminal ability, that is, criminals with a high p are more likely to evade law-enforcement than criminals with a low p. It is important to note the role of policing technology. If law-enforcement were to put systematically more effort into catching criminals of one demographic group than of another group, then this would be ultimately reflected in their respective probability of success and this is what matter to the matching partner.

Consider a frictionless market and assume that a criminal observes the probability of success of his partners. In practice, communication between criminals is tricky as it bears risks: talking about an illegal activity with an undercover agent, having witnesses, deciding whom to meet in person. Information and meeting frictions are discussed in the last subsection. Thus, a match emerges only if both parties judge one another to be trustworthy. In this model the easiest way to trust a partner is by making sure he doesn't get arrested.

Assume that criminals are conscious that they are playing a two stage game. In the first stage they choose a partner. After that the probability of success is realized and in the second stage, if at least one partner is arrested, they play a prisoner's dilemma. The second stage has been extensively analyzed in economics, and the dominating strategy for both partners is to cooperate with the prosecutor and "spill the beans" on the other. However, if none of the two partners is captured, the game ends. Solving backwards, it seems best for a criminal to select a partner who is less likely to get arrested, underpinning the incentive for positive assortative matching.

In the following expected utility representation, I model the first stage of the game. Without loss of generality, assume that criminals are ordered as 1 and 2 in a partnership. For simplicity, criminals commit crimes with partners and if they don't find a partner they prefer to work in the legal sector with wage W. A criminal with probability of success p_1 maximizes his expected utility with respect to his partner's success probability p_2.

If criminal 1 gets arrested he gets a disutility $D_1 > 0$. If he does not get arrested he will get the exogeneous[11] individual return $Y \geq 0$. In the special case when his partner gets arrested he will get the same return because they would have already parted and shared the loot, but he will also incur the disutility $D_2 > 0$ for the fact that his partner was arrested[12]. The parameters D_1, D_2 and Y are assumed to be crime-specific and do not vary systematically with respect to different probable partners. For example if a criminal decides to rob a bank he knows that he would earn a certain amount no matter the partner and because of the crime he would face a disutility if his partner gets caught. Additionally, one can think of D_2 coming from a fixed criminal role, for which cooperation is required. This is most easily seen in the example of an armed robbery, where one partner holds the weapon and the role of the other is to be an escape driver. In this example, any other potential partner can be an escape driver and his arrest would have similar implications on the probability of success of the robber. Still, a driver with a low probability of arrest is more desirable than a driver with a high probability of arrest. Thus, the expected utility is of the following kind:

$$\begin{aligned} EU(p^2) \;=\; & p^1 p^2 Y + p^1(1-p^2)(Y-D_2) + \\ & p^2(1-p^1)(-D_1) + (1-p^2)(1-p^1)(-D_1) > W \end{aligned} \tag{1}$$

The expected utility is increasing in the probability of success of the partner, ensuring a preference for the most successful partner ($\frac{\partial EU}{\partial p^2} = p^1 D_2$). That is, the higher the criminal probability of success of the choosing criminal, the higher is the marginal utility from a match with a better partner. Given the same preference for the partner, mutual acceptance of matches ensures that each criminal will pair up with one of similar probability of success in equilibrium.

To see that $p^1 = p^2$ is an equilibrium outcome, assume that all criminals have a reservation criminal probability of success of p^1, equal to their own probability of success (only "probability"

[11] The exogeneity of income assumption is supported by criminological evidence that property crimes are often opportunity based, rather than carefully planned. See for example Alarid *et al.* (2009).

[12] Setting $D_2 = Y(1-\alpha)$ would relax the behavioral conditional independence assumption, where α is the additional probability of success in case the partner gets arrested, whose realization occurs after the matching choice has been completed, in the second stage of the game.

from now on). First, if 1 criminal deviates and lowers his reservation probability, that is, he accepts a partner that has a lower probability than him $p^2 < p^1$, then he would be worse off compared to a match with a partner of his same probability level. Second, if he would consider a partner with $p^2 > p^1$, he would be rejected, because everybody else has the strategy to match with a partner of their own probability. Third, if all criminals have a lower reservation probability than their own, then one can deviate profitably by matching up with a higher probability criminal. Fourth, if all criminals have a higher reservation probability, then nobody would agree to a match (except among $p_i = 1$) because the possible counterpart with $p^2 > p^1$ would want to match with someone of even higher probability $p^3 > p^2 > p^1$. Therefore, matching with a partner of the same probability is a Nash equilibrium (as similarly shown by Becker, 1973).

Thus, in frictionless markets positive assortative matching would imply that

$$p^1 - p^2 = 0$$

3.2 Bias

In order to analyze the issue of a bias, assume that there are M demographic groups of criminals, differing from one another in demographic characteristics (for example three groups can be black males, black females and white females). Given that a match is composed of 2 criminals, I will consider equilibrium outcomes between group m and n. The first criminal (in a match) from group m has a probability of success p_m^1, while the second criminal has a probability of success p_n^2.

The matching pattern in the market for criminals can be described through figure 1. Let the individual criminal ability p_m be distributed with mean $\overline{p_m}$ and finite variance δ_m, with support between 0 and 1[13]. In this way, within each m and n group there is a heterogeneity of ability. Consider the matches between 2 groups, m and n, and assume that $\overline{p_m} > \overline{p_n}$. In equilibrium, at the individual level the difference in ability between partners would be 0. If the distributions of ability of criminals of groups m and n are coinciding along an interval, as in figure 1, then there could be matches between the 2 groups. This is demonstrated in the gray interval in the figure, in which $p_m^1 = p_n^2$. In this case, if criminal 1 from group m draws a relative low probability with respect to his own group and criminal 2 from group n draws a relative high ability, then they can form a match. Otherwise, if the criminals do not draw a probability from the gray region, they would segregate by creating matches within their own groups, as in the right tail of the distribution of the criminals from group m. This is when matching on observables will coincide with matching on ability. Thus, with introducing different demographic groups the prediction of this model is that

$$p_m^1 - p_n^2 = 0 \tag{2}$$

This pattern of matching is similar to the one tabulated in Table 3. There, $\overline{p_{males}} > \overline{p_{females}}$. The two groups match in the common area of when $p \approx 0.627$. In the opposite tails of their respective distributions of probability of success, they match along $\overline{p_{females}} \approx 0.42$ on average for females and $\overline{p_{males}} \approx 0.64$ on average for males.

However, matching choice could also be the result of preferences. If one group has an advantage in reputation or is simply preferred to any other group, then its members would have the bargaining power to choose partners from a different demographic group with higher probability of success than their own. To see this consider figure 2. On the horizontal axis the probability of success for group m is depicted, while on the vertical axis is the probability of success for group n. The 45 degree line shows the unbiased matches, with no frictions and no bias. Consider first the case of a positive bias. When a certain criminal with a probability p_m considers partners from the other group, if his bias is positive, he will accept matches with

[13] The argument does not depend on the distributional assumption and the productivity in each group could be distributed differently.

Figure 1: Distributions of groups of criminals

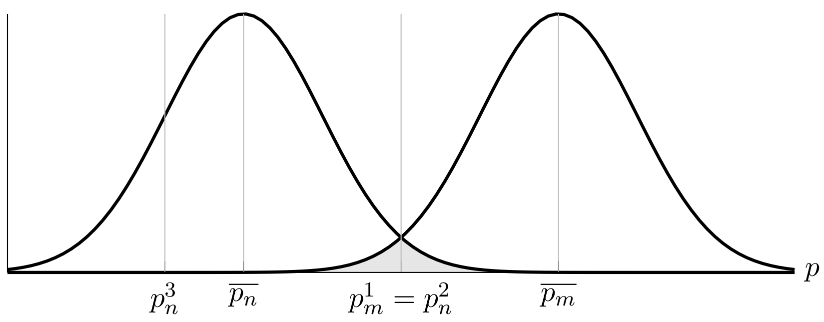
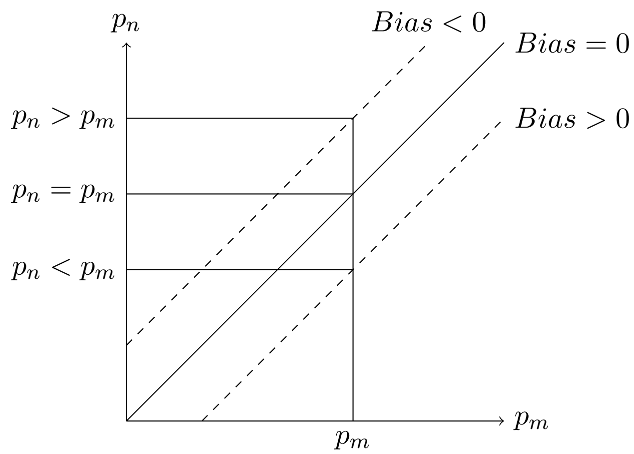


Figure 2: Frictionless Matching with Bias



Notes: On the vertical axis the probability of success of group n is depicted, and on the horizontal axis the probability of success of group m. B denotes bias in matching, the 45 degree line denotes the equilibrium along which matches are unbiased.

partners p_n that have a lower probability of success. This match would be acceptable for the other partner, because of the higher success probability of the choosing m criminal. Therefore, in this case, $p_m^1 - p_n^2 = Bias$. In the second case, if the bias is negative, p_m will demand a higher probability of success in order to match up with criminals from the n group. These matches would be rejected by criminals from group n who would prefer to match with someone with higher probability of success. Thus, criminals would match within their own demographic groups. In the third case, if there is two-sided bias compatibility, if the bias is negative and group n has a positive (compensating) bias towards group m, then criminals from the two groups would match between one another. That is, criminals from group m do not like matching with n, but criminals from group n like it. Therefore, group m would demand higher probability of success from group n and group n would be glad to give it. In this case, matches between m and n would be observed and:

$$p_m^1 - p_n^2 = Bias$$

3.3 Frictions

Clearly, the outcome of perfect positive assortative matching depends crucially on the assumption that matching is frictionless. This strong assumption is likely not satisfied and one can easily note that as frictions increase the matching becomes more dependent on opportunity rather than on planning. Shimer & Smith (2003) and Smith (2006) introduce frictions in the matching market and show that, given the positive assortative matching incentive, the difference in probability between the two partners would be close to zero in expectation:

$$E(p_m^1 - p_n^2) = 0 \tag{3}$$

There are several types of relevant matching frictions. First, partners might be impatient in waiting for a good match and they would match with the first arriving candidate. In segregated neighbourhood this would imply matching within the own demographic group. However, the data clearly shows that on average the jurisdictions of law-enforcement agencies are diverse with respect to gender and race, with an average value of 0.4 (see Table 1) and both inter-gender and inter-race partnerships exist(as in Table 2). Thus, matching with the first arriving candidate could be described by random matching. In the context of figure 1 this would imply that it would be equally likely to observe a match between criminals with probabilities of success p_m^1 and p_n^2, as it would be to observe a match between criminals with probabilities of success p_m^1 and p_n^3. Thus, random matching implies that:

$$E(p_m^1 - p_n^2) = \overline{p_m} - \overline{p_n} \tag{4}$$

At the other extreme, criminals could be very patient and wait for their perfect match, creating a pattern of matching similar to Equation 3.

A second friction could be that a criminal can choose partners only from a limited set, such as a gang, mafia or marriage. Participation in such a group implies the repetitive playing of the prisoner's dilemma, that is, the criminal that is arrested is expected to observe silence. In this case, the incentive for positive assortative matching breaks down. It might be that in big samples 4 would be valid, that is, within some groups some criminals will match positivelly, negativelly and randomly. Jumping fast-forward on empirics, I try to capture this in two ways in my robustness checks. First, repetitive outcomes would be captured by the agency-specific fixed effects. Second, the data offers the unique opportunity to control for gang membership.

A third friction is that the perspective of high earnings can make for unlikely bedfellows. In this case, matching could follow any pattern, yet I conjecture it could not depend on observables. The prospect of high earnings is similar to impatience, thus earning a pattern closer to random matching. In a robustness check I show that accounting for this friction does not change the results.

Fourth, imperfect information about the partner can lead to several outcomes. On one hand, if there is no information, then matching would be as random, because no criminal has information on possible partners. On the other hand, if there is full information, then matching would be unbiased because each criminal could observe the other perfectly. Thus, the difference in probability of success between the two partners would vary from random to zero. In a related case, informational frictions, such as reputation, can underpin a discriminatory bias and produce statistical discrimination - a bias that diminishes as the criminal ages and obtains information about the probability of success of the opposite demographic group. This concern is addressed in the robustness checks.

Therefore, in positive assortative matching with frictions in some cases one can expect a difference in the probability of success between partners varying from zero to the difference in average probability of success between the two demographic groups. Matching varies from unbiased to random and in many cases does not imply that the difference in probability of success between partners is correlated to the observable characteristics. While I have addressed some of these frictions in the robustness checks, it is important to bear them as a potential caveat to my results. The next section formally defines the empirical hypotheses and test for identifying a bias.

4 Empirical strategy

4.1 Hypothesis

The positive assortative matching pattern in the model from the previous section is based on the assumption that criminals match endogenously on criminal ability characteristics, that are unobservable to the econometrician. Once a match has been established and the crime commited, both partners face the same probability of success, conditional on the crime incident. Taking the difference between the two probabilities cancels out the incident specific effect, which includes distance from law-enforcement agents, number of policemen on patrol on the day of the crime, crime characteristics and other characteristics of the partnership, as well as location specific effects[14].

Under unbiased matching, the difference between the two success realizations should be zero on average and not correlated with observables, that is, the correlation between the difference in observable traits and the difference in observed probability of success should be zero. If β is the regression coefficient on the difference in observable traits with dependent variable the difference in probability of success, then

$$H_0 : \beta = 0$$

As already outlined in the previous section, if the matching environment is characterized by frictions, then matching would not be positive assortative but close to random and exogenous. In an extreme case each criminal matches with the first partner he meets. In this setting, the difference between two partners could be predicted by the demographic averages of their group. For example, if black males have a higher success probability than white males, then if one draws randomly criminals from each group, on average the black male would be of higher criminal ability than the white one. Therefore, the matching choice is correlated with observable characteristics and under the alternative:

$$H_1 : sign(\beta) = sign(\overline{p_m} - \overline{p_n} > 0)$$

In the third scenario, the matching choice could be biased and driven by an observable characteristic. Considering the sign of β, $\beta > 0$ could be due to both bias and frictions. But if $\beta < 0 < \overline{p_m} - \overline{p_n}$ then the negative bias effect dominates the frictions in the market. Therefore, the negative bias leads to productivity differences within the couple that run counter to the ones between the two demographic groups,

$$H_2 : \beta < 0 < \overline{p_m} - \overline{p_n}$$

4.2 Identification

In order to test the hypotheses outlined in the previous subsection I estimate the specification:

$$p^1 - p^2 = (X_1 - X_2)\beta + \upsilon \tag{5}$$

where the observed difference between success realizations p^1 and p^2 is a function of $X_1 - X_2$, the net difference in observable characteristics. X contains the variables for race, gender and age with reference category black males. The dependent variable $p^1 - p^2$ can take the values $\{-1, 0, 1\}$, depending on whether the first partner was arrested (and the second succeeded), both of them faced the same outcome, or, the second partner was arrested[15]. The coefficient β measures the correlation between the observed success differences between the 2 criminals in

[14] Location specific fixed effects are included in the robustness checks.

[15] For a treatment on the latent nature of the dependent variable and estimation see appendix.

the couple and the difference in observable traits.[16].

In the following empirical analysis a couple corresponds to one observation and not to two, as is the case with dyadic data analysis, which is used to model the occurrence of an event between 2 persons or countries. For example, in network theory the establishment of a link between 2 entities (nodes) is modeled from the perspective of both entities. Here this is not the case due to one concern: there is no variable denoting an interaction that differs for the 2 nodes, so there would be issues with multicollinearity were I to use dyadic analysis in this case. In this vein, it is important to note that law-enforcement agencies do not seem to follow a specific pattern in recording the order of criminals in an incident and records are as if randomly assigned. Nevertheless, I randomize their order[17]. Therefore, there is no statistical difference between all criminals 1 and 2 in a couple[18].

Ideally, one would want to have several observations over the same criminal pair in order to pinpoint the fine difference between p_m and p_n in a match. The lack of such detail in the data is compensated by many observations, that can relate the systematic differences between match partners to observable traits. Therefore, I identify aggregate βs for the demographic groups and the identification for the independent variables comes from observations in which only one of two partners was arrested.

5 Results

The first column in table 4 presents the baseline results from the estimation of equation 5. The following columns show diverse robustness checks which will be discussed in the next section. The coefficient on *white* is negative, while the coefficient on *female* is positive. The interpretation of the coefficients is discussed below. To show the significance of the results, in table 5 they are presented within the context of the group success means. The first 2 columns show the unconditional values of p^1 and p^2, in the sample[19]. The last two columns show the predicted differences, following equation 5.

In male-female groups females have a higher probability of success. The coefficient on *female* is positive, and the independent variable is negative. In more detail, in a male-female couple $female_1 = 0$ and $female_2 = 1$, where $female_1$ and $female_2$ are dummies for both partners for female genders. Therefore, *female*$= female_1 - female_2 = 0 - 1 = -1$. The variable that denotes the difference in demographic characteristics is $female_2$, which enters the equation with a negative sign. Thus, $p^1 - p^2 = \beta \times (-1) < 0$ showing that on average females are less likely to get arrested when they are in a male-female group.

Consider the pair of a black male and a black female. For them the dependent variable should be positive, because on average black males face a higher probability of success than black females, as seen in table 5. Therefore, $p_{blackmale} - p_{blackfemale} > 0$ in such a match. However, the coefficient on female is positive meaning that $\widehat{p_{blackmale} - p_{blackfemale}} < 0$. Therefore, on average black females have lower probability of success than black males, but whenever they form a cross-gender partnership they have a higher probability of success. A similar pattern can be observed in the white male and female pair, where while white males have a higher likelihood of success, in the observed matches they are of a lower criminal quality. Therefore, for matches

[16]Another way to measure this would be to estimate β_1 on X_1 and β_2 on X_2, where by construction $\beta_1 = -\beta_2$. The symmetry is present when estimating as a robustness check a specification with separate β's for the two offenders. The reason for which I estimate the coefficient β on $X_1 - X_2$ is because it provides directly a statistic, comparable to the difference in success productivity between the groups defined by X.

[17]I generate a uniform distribution for the first criminals in each couple and reassign them to be second if their realization is above the mean.

[18]I don't show a table with a test for the difference in means for the demographic variables because the information in it would repeat the summary statistics.

[19]The success means remain the same when conditioning on agency origin, one of the spoils of large samples.

between males and females the null hypothesis of unbiased matching is rejected, as well as the alternative of random matching as a result of frictions.

However, the hypothesis of bias cannot be rejected. The observed patterns in male-female matches are consistent with males having a negative taste for working with females and with females having a positive bias for male criminals.

In a black-white couple whites are more likely to get arrested. The estimated coefficient on race *white* in table 4 is negative, meaning that in black-white couples blacks have a higher probability of success. This is also consistent with success means in table 5. Therefore, I reject the hypothesis of unbiased matching, but I cannot reject the alternative hypotheses of random matching and positive (or negative) bias. Either white males form matches with the first black male they meet, and or black males have a positive bias for whites and or white males have a negative bias against blacks.

With respect to age, I cannot reject the null hypothesis of unbiased matching. Criminal success is increasing with respect to age and 25 year olds have a higher success mean than 18 year olds. Random matching would generate a positive coefficient for old-young partnerships. Given that the coefficient is not different from 0, I can reject the alternative hypothesis of random matching and biased preferences.

In sum, I find evidence of biased preferences in matches between males and females. Matches between whites and black could be generated by biased preferences and market frictions. Matches with respect to age seem to be as if generated from an unbiased matching environment. The following section will assess the effects of measurement errors and reporting biases, market specific trends, size of the monetary criminal earnings, age effects and other robustness checks.

6 Robustness checks

In this section I present robustness checks. First, in column 2 of table 4 I present estimates with interacted fixed effects for month and reporting agency. These fixed effects would hold constant market specific matching frictions like specific within gang matching. If for example in one market whites always match with blacks and the matches have always the same systematic outcome, then the fixed effects would cancel out this variation. Even though, these location crime specific effects are canceled out in the differencing of the successes between the 2 partners, the difference itself might vary systematically across the jurisdiction of different law-enforcement agencies. In column 2 it is shown that results remain the same.

Second, measurement error for non-arrested couples could impact the estimates, because of reporting bias towards the non-arrested. For example, maybe the non-arrested were not observed as well as those who were arrested. In order to assess this issue, I exclude the non-arrested from the sample and estimate again equation 5. Thus, the underlying sample consists of couples in which both partners were arrested and couples in which only one of two partners was arrested. The results are presented in column 3 of table 4. Coefficients do not change in sign, but they increase in absolute terms. This could be due to two reasons: either the measurement error attenuates estimates, or, in this way I exclude the group of couples that face the same arrest outcome and that were less likely to select one another on observable characteristics. This robustness check also diagnoses the measurement error due to a specific reporting bias with respect to black males. The average probability of success for black males could be lower than recorded, because there could be less real black male criminals than the ones reported. In this subsample the success means are ordered as black males having the largest success probability, followed by white males, black females and white females[20]. Given that the success ordering is the same as in table 5, also the results remain unchanged and robust to these specific biases.

In column 4 of table 4 I include the monetary return on a crime as a covariate. The size of the stolen loot could imply "impatient" matching - if a given criminal target earns a high

[20]The exact numbers are $p_{BlackMale} = .165$, $p_{WhiteMale} = .130$, $p_{BlackFemale} = .115$ and $p_{WhiteFemale} = .103$

enough monetary return for the able criminal, he would be ready to match randomly with the first arriving partner. Therefore, for high levels of stolen loots matching would be random. Or, alternatively, for a high loot one would be more picky about his criminal partners. Also in this case results remain unchanged.

In column 5 the sample is limited to partnerships whose members are older than 29 years. These offenders are more experienced, their disutility of arrest could be larger than the average because of an extensive police file and the quality of the pairing should be better. There is a persistent negative effect for whites, but the effect for females is close to 0. This implies that I cannot reject the null hypothesis of unbiased assortative matching. If one is willing to assume that the bias is discriminatory, then the results could imply that the bias for females is statistical discrimination that diminishes as both partners age and learn about the quality of the other's demographic group.

In column 6 the sample is limited to those crimes that were reported to have occurred in daylight hours, between 8 and 19. This check minimizes the reporting bias due to the cloak of the night. In these crimes at least one of the offenders was arrested (thus, subsample of the sample in column 3) and results are similar in magnitude to the ones in column 3.

One of the channels of relaxing search frictions in the crime market is to search for partners within the own gang. In column 1 of table 6 I control for gang affiliation, which would ease the formation of partnerships and it does not change results. The variable for gang is negative but not significant. The negative coefficient shows that in matches of non-gang and gang members, the gang ones are more likely to get arrested. This could be either due to inherent differences between individual criminals and criminals from gangs, where the former are less likely to get arrested, or, law-enforcement has an easier access to gangsters due to for example informants. A robustness check on only gang members shows similar results (not included for brevity).

In column 2 I include the full choice set of races and results remain the same and none of the additional variables show a significant correlation to differences in success.

In column 3 I control for same offense - both criminals have the same offense code on their incident record. If criminals are specialized and commit the same offense they would be better able to judge one another. Furthermore, if there is a male-specific intimidation effect that drives the results for the female bias, it would be reflected in the offense code for the male and, once this source of variation is canceled out, the coefficient on female should reflect the average productivity differences between the 2 groups and be negative. However, results remain the same and are, therefore, not driven by crime role.

In order to partially disentangle learning from all reasons for matching, I restrict the sample by the age differences between 2 offenders. In column 4 of table 6 the sample is restricted to only those pairs whose age difference within is less than 5 years[21]. The age variable shows a significant direction, hinting that older offenders are less successful, while the coefficient on race is lower. This is consistent with the hypothesis for a bias for older partners, where they turn out to have a lower criminal ability than the younger one. This age effect could be also due to strategic policing, especially when both offenders are young and the older one is considered to be the "bad influence", or, because the older offender is more likely to have a file with the police. This effect, albeit smaller, is also to be found in column 5 in table 4, where I considered partnerships between older criminals.

In column 5 I exclude observations from a given agency-year in which the observed partnerships were only between blacks or between males. Such a criminal market would suffer from non availability of other partners and the results remain the same, given that identification comes from the pairs with differing observables. In column 6 I aggregate the agencies into cities and control for city-month fixed effects. The results remain robust throughout all specifications.

In column 7 I present results where the underlying sample is composed of groups of 3. Each

[21] The choice of age gap is arbitrary, but representative of the results that the reader can find in the appendix for different gaps.

group is represented by 3 observations of 2 randomly assigned partners, consistent with the intuition that each member has to match with each other member. The results are the same as in a group of 2. This could be interpreted as that the same type of matching mechanisms that governs the pairing up of 2 criminals could account for the formation of small criminal groups and gangs.

Disaggregating the results by crime types in table 7 shows that the effect for whites is observed in shop-lifting. The effect for females is driven by robberies and other larceny and stolen property offenses. The effect for burglaries, motor vehicle theft, theft of parts and from motor vehicles is not conclusive as females have a higher success probability than males in these crimes. Surprisingly, there is barely an effect for females in shoplifting, a crime traditionally associated with their gender. This could be due to there being no negative bias for females, consistent with their associated reputation, but it could be also due to matching frictions. The coefficient is close to zero, so it could imply also unbiased matching. Across crimes the age variable changes sign. In shoplifting it is negative, so that in crime commited by a 17 year old and a 18 year old, the older one is more likely to get arrested. Conversely, in an auto theft the younger criminal is more likely to get arrested.

Further on, in the appendix one can find robustness checks extending columns 4 and 5 from table 6, estimation on samples selected by relative diversity of the underlying criminal population and results from multinomial logit estimation of equation 5, as well as, separating the coefficients for the 2 criminals.

7 Conclusion

This paper analyzes partnerships among criminals and provides evidence for discriminatory bias in matching between males and females. In the context of breaking the law, the practice of the police offering a bargain (or a dilemma) to the offender that was first apprehended in order to catch his partner creates an incentive to choose as one's partner the best from all possible candidates. Therefore, I model matching by assuming that the desired partner trait is a high ability to escape law-enforcement. This incentive leads both partners to choose a successful counterpart, thereby creating a pattern of positive assortative matching between criminals on probability of success. Arrest realizations allow me to pinpoint matches in which criminal productivity differs. Whenever only one of two partners got arrested this might hint on there being a difference with the criminal skills of the partners. If this difference is correlated with observable characteristics this might be evidence for a discriminatory bias.

Therefore, I identify biases based on the endogenous decision with whom to match. Discrimination is observed whenever one partner differs from another in an observable characteristic and faces a different probability success. In the case of gender, whenever females form a partnership with males they face a lower probability of arrest than males. Taking this together with the observation that on average females face a higher probability of arrest than males, means that in male-female matches females match down. This is consistent with females having a positive taste or bias for males and males having a negative bias for females.

Similarly, blacks have a higher success average and when they form a partnership with whites they still face a higher success probability. Given assortative matching, this is consistent with matches forming in an environment with search frictions, where the selection of the partner is close to random.

Additionally, I find that the discriminating differences in productivity diminish for older criminals hinting at the hypothesis of statistical discrimination between males and females. I find an additional discriminatory bias between peers of similar ages, where if a 20 year old criminal forms a partnership with a 17 years old one, then he faces a higher likelihood of arrest. This hints at a pattern where the younger one compensates for his age with a higher criminal ability. Other robustness checks include limiting the analysis to criminal market with demographically diverse offender pool and controlling for measurement errors by considering only couples where at least one person was arrested or the crime was commited in broad daylight and controlling for the size of the loot.

The novel empirical design conveys the essential message that considering positive assortative matching as characterizing matches, and taking into account productivity differences between demographic groups, one can refer systematic differences in criminal ability within a match to biased preferences on observable traits or search frictions. The identification comes from the endogenous match formation, and by virtue of arrest revealing criminal ability. Conceptually assortative matching and discrimination are linked through the significance of observable traits in the matching choice. When choosing a partner based solely on criminal ability, observables should not predict significantly the partner choice. When matching is based on an observable trait, as in discrimination, then assortative matching on criminal ability fails. Essentially, my empirical strategy determines whether matching is based on observables in the presence of incentives to match on ability.

This paper links assortative matching with discrimination in a novel test for bias. It makes a first step in describing matching patterns in the illegal criminal market, linking the crime literature with the literature on assortative matching and discrimination. The implication of this paper are several. First, matching between whites and blacks is close to random and persisting with age. This allows for an application in cell-mate assignment in prison, where cell-mates could be of different race colour. Second, this paper offers a perspective into the creation of cross-gender pairs in a formal relationship in an unregulated market. A similar market is the one for academic article co-authors, where females could be better at producing articles than males in a male-female co-authorship. In this market the relative productivity of females cannot be teased out because the outcome is pair-specific and not individual-specific as in crime, which spells out the advantage of my application in identifying a discriminatory bias.

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Table 4: Matching patterns

	(1) p^1-p^2	(2) p^1-p^2	(3) p^1-p^2	(4) p^1-p^2	(5) p^1-p^2	(6) p^1-p^2
White	-0.005***	-0.005***	-0.010***	-0.005***	-0.006**	-0.005***
	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)	(0.002)
Female	0.007***	0.007***	0.017***	0.006***	0.002*	0.005***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Age	-0.000	-0.000	-0.000	-0.000	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(loot)				-0.000		
				(0.000)		
Constant	0.000	0.000***	0.000	0.001	-0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	1,087,371	1,087,371	504,750	990,956	221,935	657,168
R-squared	0.000	0.197	0.000	0.000	0.000	0.000
Month*Agency FE	-	x	-	-	-	-
Sample Restriction:	.	.	Only Arrested	Loot	Age≥30	7<Hour<20

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Errors clustered at the reporting agency level. The top of the column shows the dependent variable. Estimation through OLS, it includes interacted year month and agency fixed effects where noted with "x".

Table 5: Differences table

	Unconditional success means		Regression results	
Type of Couple	p^1	p^2	$\widehat{p^1-p^2}$	Standard Error
Black Male-Black Male	0.708	0.708		
Black Male-Black Female	0.708	0.513	-0.007***	0.001
Black Male-White Male	0.708	0.590	0.005***	0.001
Black Male-White Female	0.708	0.506	0.003*	0.001
Black Female-Black Female	0.510	0.513	0.000	0.000
Black Female-White Male	0.510	0.590	0.012***	0.002
Black Female-White Female	0.510	0.506	0.005***	0.001
White Male-White Male	0.591	0.590	0.000	0.000
White Male-White Female	0.591	0.506	-0.007***	0.001
White Female-White Female	0.505	0.506	0.000	0.000

Notes: p^1 and p^2 denote the unconditional probabilities of success. $\widehat{p^1-p^2}$ denotes the difference in success means as predicted by equation 5

Table 6: Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$p^1 - p^2$	$p^1 - p^2$	$p^1 - p^2$	$p^1 - p^2$	$p^1 - p^2$	$p^1 - p^2$	$p^1 - p^2$
White	-0.005***	-0.005***	-0.004***	-0.004***	-0.005***	-0.005***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)
Female	0.007***	0.007***	0.006***	0.007***	0.007***	0.007***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Age	-0.000	-0.000	-0.000	-0.002***	-0.000	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Gang	0.005						
	(0.003)						
Indian Race		-0.006					
		(0.005)					
Asian Race		-0.000					
		(0.005)					
Constant	0.000	0.000	0.000	0.000	0.000	0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	1,087,371	1,107,681	915,811	756,106	973,307	1,087,359	720,372
R-squared	0.000	0.000	0.000	0.000	0.000	0.169	0.329
Month*City						x	
Incident FE							x
Sample Restriction:			Same Offense	Age Gap$<$5	Diversity > 0		Triple Matching

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Errors clustered at the reporting agency level. The top of the column shows the dependent variable. Estimation through OLS, including fixed effects where noted. In column 5 the sample includes agencies that are heterogeneous in at least one dimension between gender and race. Column 6 includes interacted year month city fixed effects instead of year-month-agency and errors are clustered at the city level. Column 7 present results on an underlying sample of groups of 3, with group (incident) fixed effects and errors clustered at the agency level.

Table 7: Results by Crime Type

UCR Code	Crime	White		Female		Age		Constant		Observations	R-squared
200	Arson	-0.017	(0.020)	0.021*	(0.012)	0.001	(0.001)	-0.006	(0.005)	5,270	0.001
23A	Pocket-picking	-0.006	(0.019)	0.007	(0.010)	0.001	(0.001)	-0.002	(0.006)	2,074	0.001
23B	Purse-snatching	-0.006	(0.016)	-0.014	(0.011)	-0.001	(0.001)	-0.003	(0.006)	3,344	0.001
23C	Shoplifting	-0.008***	(0.002)	-0.003*	(0.001)	-0.001***	(0.000)	0.000	(0.001)	300,639	0.000
23D	Theft from Building	-0.007	(0.004)	0.001	(0.002)	0.000	(0.000)	0.000	(0.001)	80,179	0.000
23E	Theft from Coin-Operated Machine	-0.087*	(0.048)	0.046	(0.035)	-0.001	(0.001)	0.003	(0.005)	2,988	0.010
23F	Theft from/of Motor Vehicle	-0.004	(0.006)	0.022***	(0.004)	0.001**	(0.000)	0.000	(0.001)	63,083	0.001
23G	Parts	-0.009	(0.011)	0.028***	(0.010)	-0.000	(0.000)	-0.001	(0.003)	14,123	0.001
23H	All Other Larceny	-0.005*	(0.003)	0.005***	(0.001)	0.000***	(0.000)	-0.000	(0.001)	199,944	0.000
240	Motor Vehicle Theft	0.008	(0.007)	0.026***	(0.004)	0.001***	(0.000)	0.000	(0.002)	53,662	0.002
220	Burglary	-0.004	(0.003)	0.016***	(0.002)	0.000	(0.000)	-0.000	(0.001)	169,941	0.001
120	Robbery	-0.006*	(0.003)	0.017***	(0.004)	-0.001**	(0.000)	0.001	(0.001)	112,292	0.001
280	Stolen Property Offenses	0.014	(0.010)	0.019***	(0.005)	0.000	(0.000)	0.001	(0.003)	19,668	0.001

A Specification

In more detail, the regression specification in the main text is:

$$p^1 - p^2 = \alpha + \beta_w(W^1 - W^2) + \beta_f(F^1 - F^2) + \beta_a(A^1 - A^2) + \epsilon \tag{6}$$

where 1 and 2 refer to the order of the criminals in the partnership. W is an indicator variable for white skin colour, F is an indicator variable for the female gender. A is age, measured in years. The outcome variable is latent: $p^1 - p^2 \in \{-1, 0, 1\}$, while it is defined over the interval $[-1, 1]$. This means that the error term is not normal, as it is assumed with OLS, but it has mass around $\{-1, 0, 1\}$. Therefore, as a robustness check I estimate equation 6 with a multinomial logit estimator.

The first 2 columns of table A.1 repeat the results from table 4 from the main text. The first column shows the baseline results. The second and third columns show the estimation results for a multinomial logit model with base outcome 0. The results are in line with the ones in the first 2 columns and the marginal effect follow the pattern of the signs of the coefficients in OLS. For example the marginal effect for white is positive (.0025) for the relative outcome of $p^2 > p^1$ with respect to $p^2 = p^1$. Therefore, in the situation of the first criminal becoming white (very hypothetical), while the second is black, there is an increased likelihood that $p^2 > p^1$. The last column presents results estimated with an ordered logit, that takes into account the latent nature of the dependent variable. The results are similar to the ones provided with the previous 2 estimators.

The alternative specification considered in this section is:

$$p^1 - p^2 = \alpha + \beta_w^1 W^1 + \beta_w^2 W^2 + \beta_f^1 F^1 + \beta_f^2 F^2 + \beta_a^1 A^1 + \beta_a^2 A^2 + \epsilon$$

where $\beta^1 = -\beta^2$ by construction. This symmetry condition is sensitive to the random order of criminals within a couple. However, when taking several random orders and taking the mean estimates, it seems that the mean estimate for white is 0.004 and for female 0.007, both significant. Table A.2 presents the results. The first column shows estimates with no fixed effects and column 2 shows that the point estimates do not change with the inclusion of location-year specific fixed effects.

Considering a black male and female couple, the dependent variable becomes negative, showing that the probability of success of the female is higher than that of the male. Similarly, in a male white and black couple the probability of success of the white criminal is lower than that of the black. These results are in line with the results in the main text. The last 2 columns show the estimation results for a multinomial logit model. They are in line with the results in the previous column. For example the marginal effect for the variable White 2 for a positive outcome variable is positive (0.003). When the second person in the pair is white it is more likely that the probability of success of the first black male is bigger than the probability of success of the second white male. The marginal effect for the second criminal to be a female is -0.005. Only the variable for age seems to show different results than in the previous specifications, the marginal effect for age of both criminals is positive (.00018 to .00022) for both relative outcomes.

B Evidence of Non-random Matching

A further evidence of bias or search frictions can be easily seen with the following reasoning. Consider the probability of observing a pair of two different types:

$$Pr(type_1, type_2) = Pr(type_1)Pr(type_2|type_1)$$

Table A.1: Multinomial Logit Estimates

	(1)	(2)	(3)	(4)
	$p^1 - p^2$	$p^1 - p^2$	$p^1 - p^2$	$p^1 - p^2$
Outcome		-1	1	
White	-0.005***	0.032**	-0.046***	-0.042***
	(0.001)	(0.016)	(0.015)	(0.012)
Female	0.007***	-0.068***	0.057***	0.066***
	(0.001)	(0.010)	(0.010)	(0.009)
Age	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)
Constant	-0.000	-2.718***	-2.716***	
	(0.000)	(0.023)	(0.024)	
Cut 1				-2.782***
				(0.022)
Cut 2				2.780***
				(0.022)
Observations	1,087,371	1,087,371	1,087,371	1,087,371
R-squared	0.000			
Estimator	OLS	ML	ML	OL

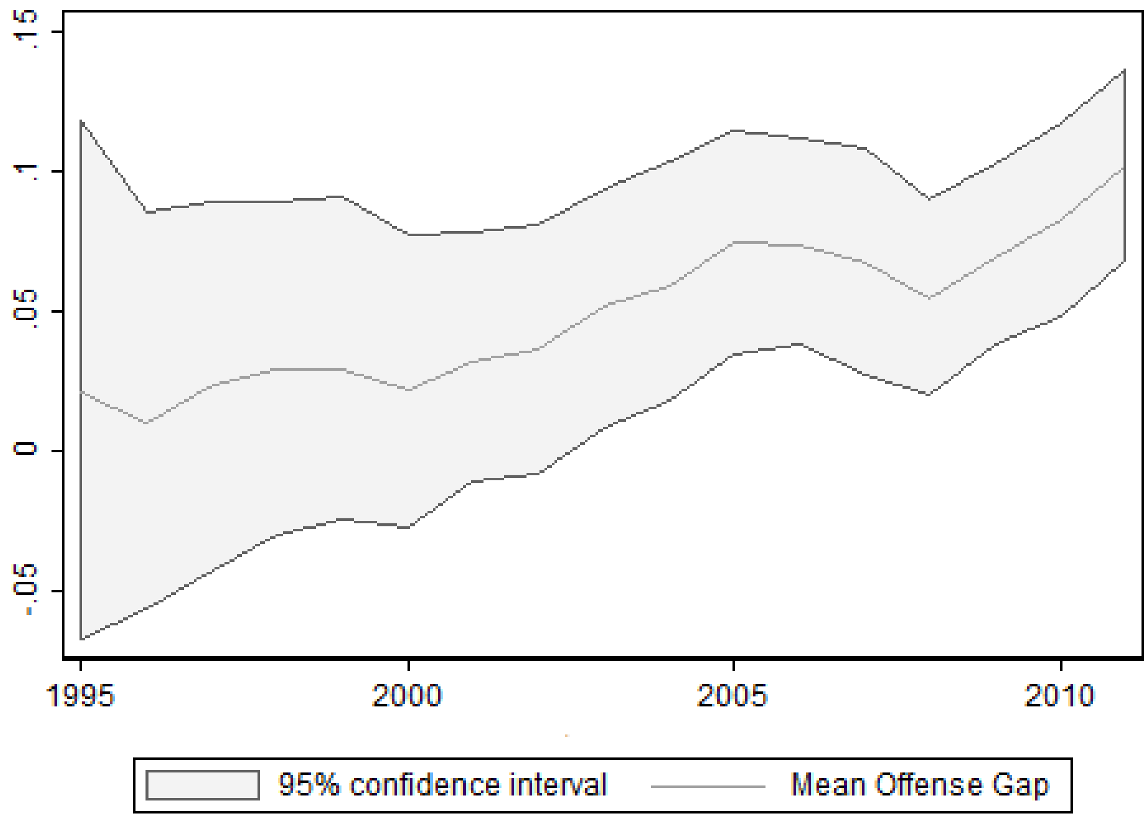
Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Errors clustered at the reporting agency level. The top of the column shows the dependent variable. The first column repeats the results from table 4. The second and third columns show the results of a multinomial logit model estimation with base outcome 0. The fourth column shows the results from an ordered logit estimation.

Table A.2: Results with a Different Specification

	(1)	(2)	(3)
	$p^1 - p^2$	$p^1 - p^2$	$p^1 - p^2$
Outcome		-1	1
Criminal 1:			
White	-0.004***	0.036	-0.028
	(0.001)	(0.023)	(0.024)
Female	0.006***	-0.109***	-0.003
	(0.001)	(0.026)	(0.020)
Age	-0.000	0.005***	0.004***
	(0.000)	(0.001)	(0.001)
Criminal 2:			
White	0.005***	-0.029	0.064***
	(0.001)	(0.024)	(0.022)
Female	-0.008***	0.025	-0.116***
	(0.001)	(0.021)	(0.024)
Age	0.000	0.005***	0.005***
	(0.000)	(0.001)	(0.001)
Constant	0.000	-2.937***	-2.936***
	(0.001)	(0.059)	(0.057)
Observations	1,087,371	1,087,371	1,087,371
R-squared	0.000		
Estimator	OLS	ML	ML

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Errors clustered at the reporting agency level. The top of the column shows the dependent variable. The first column matches the results from table 4. The second and third columns show the results of a multinomial logit model estimation with base outcome 0.

Figure 3: Bias against Matching with Males

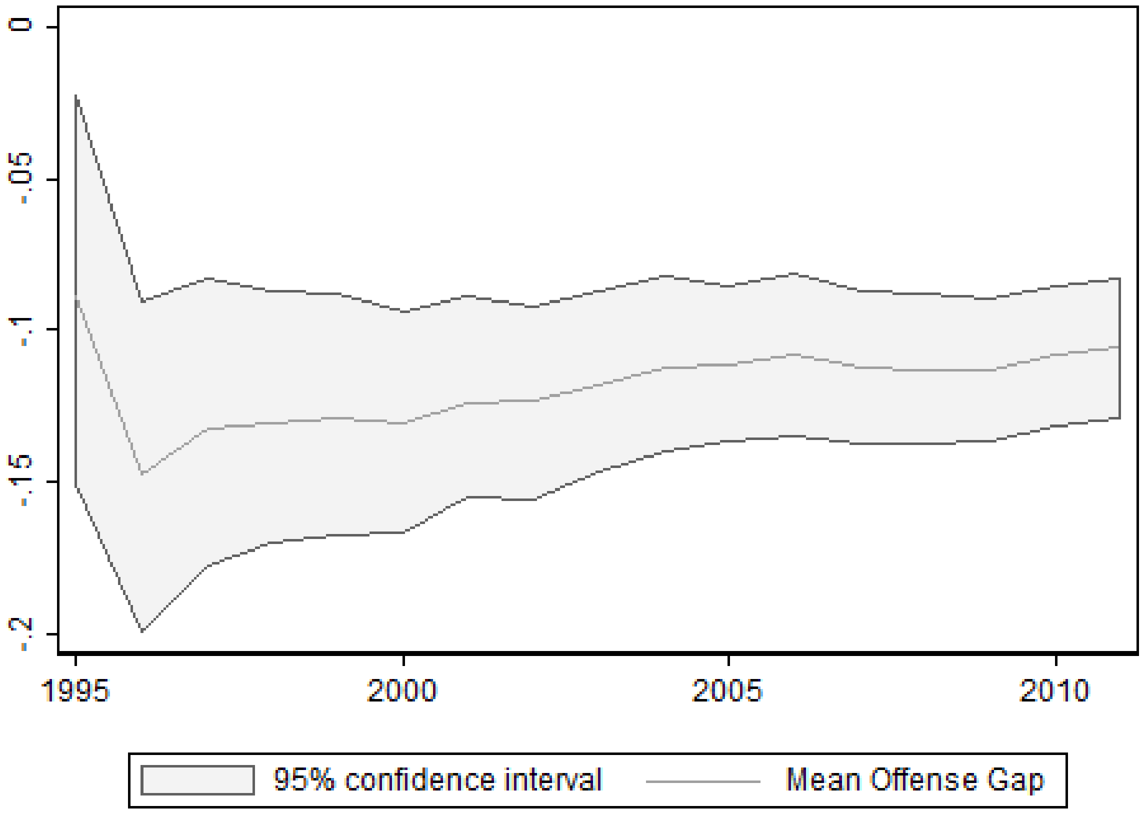


Note: This figure plots the gap $Pr(female, male) - Pr(female) \times Pr(male)$. Whenever the gap differs from 0 this is an evidence of a bias in matching. The confidence intervals are constructed through 1000 bootstrap draws of 10 000 observations each. The probabilities are averaged over the reporting agency. The larger confidence intervals at the beginning of the sample may reflect the ongoing collection effort of NIBRS, as the observations in 1995 are less than in 2011.

where type can be either gender or race and the subscripts refers to the 2 possible realizations. If 2 partners match up randomly, then $Pr(type_2|type_1) = Pr(type_2)$. The probability of ending up with a female partner would be independent from the own gender, or in other words, the unconditional probability would be equal to the probability, conditional on the type of the other criminal. $Pr(female, male) < Pr(female)Pr(male)$, indicating that $Pr(female|male) < Pr(female)$ and thus the choice for a female with whom to form a match is not independent of own type. The same pattern can be observed also in the dimension of race, showing that matching is far from random. In both figures, correlational evidence shows that criminals do not form partnerships randomly with respect to observable characteristics.

C Further Robustness Checks

Figure 4: Bias against Matching with Blacks



Note: This figure plots the difference $Pr(white, black) - Pr(white) \times Pr(black)$. Whenever the gap differs from 0 this is an evidence of a bias in matching. The confidence intervals are constructed through 1000 bootstrap draws of 10 000 observations each. The probabilities are averaged over the reporting agency. The larger confidence intervals at the beginning of the sample may reflect the ongoing collection effort of NIBRS, as the observations in 1995 are less than in 2011.

Table C.1: Varying Market Heterogeneity

	(1)	(2)	(3)	(4)	(5)
	$p^1 - p^2$	$p^1 - p^2$	$p^1 - p^2$	$p^1 - p^2$	$p^1 - p^2$
White	-0.005***	-0.004***	-0.006***	-0.003	-0.006**
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
Female	0.006***	0.006***	0.006***	0.006**	0.008***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)
Age	-0.000*	-0.000**	-0.000*	-0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.000	0.000	0.000	-0.001	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Observations	753,796	543,685	271,639	108,713	543,664
R-squared	0.000	0.000	0.000	0.000	0.000
Diversity	>0	>percentile 50	>p75	>p90	<p50

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Errors clustered at the reporting agency level. The top of the column shows the dependent variable.

Table C.2: Varying Ages

	(1) $p^1 - p^2$	(2) $p^1 - p^2$	(3) $p^1 - p^2$	(4) $p^1 - p^2$	(5) $p^1 - p^2$	(6) $p^1 - p^2$
White	-0.004***	-0.004***	-0.005***	-0.004**	-0.006***	-0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Female	0.007***	0.007***	0.007***	0.009***	0.006***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.002***	-0.003***	-0.005***	-0.007***		
	(0.001)	(0.001)	(0.001)	(0.001)		
Constant	0.000	0.001	0.000	0.001	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Observations	756,106	698,101	616,360	495,573	301,773	1,087,371
R-squared	0.000	0.000	0.000	0.000	0.000	0.000
Sample Restriction:	Age Gap<5	4	3	2	1	Age Dummies

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Errors clustered at the reporting agency level. The top of the column shows the dependent variable.