Uncovering the Gender Participation Gap in the Crime Market

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Abstract

Using data from the U.S. National Incident Based Reporting System we document a gender gap in the number of crimes committed in the property crime market: only 30% of the crimes are committed by women. Starting from the classical Becker's model on crime we investigate some potential reasons for the participation gap looking at the differential in- centives, measured in terms of earnings and probability of arrest. We observe that women obtain on average 32% less criminal earnings and face a 10% higher probability of arrest with respect to males. Once we account for type of crime and the attributes of offending, such as weapons, we find that the earnings gap is zero on average, while females still face a 1% higher probability of arrest than males. We also observe that females sort into offense types, characterized by a lower variation in the earnings risk, which reveals that females in the crime market are more risk averse than males. Furthermore, we analyze the participation gap by looking at the perceived incentives. We estimate the elasticities of crime with respect to the expected earnings and to the expected probability of not being arrested for both genders. We find that males respond to both these incentives, while females respond less to the incentive for higher earnings than males and they do not respond to the probability of arrest. Finally, we use a Blinder-Oaxaca type decomposition technique to measure crime differ- entials between females and males that arise due to different responses to incentives. We find that, in a counter factual scenario where the female elasticities increase to the level of the male ones, women would commit 40% more crimes than they actually do, reducing the male-female participation gap by almost 50%.

Keywords: Participation Gap, Gender Discrimination, Crime
JEL Classification: J71, J16, K42

1 Introduction

In the Handbook of Labour Economics, Freeman (1999) acknowledges the gap in studies about the gender variation in crime and underlines that there are no studies by economists that analyze the large difference in the participation of men and women in crime activities looking at incentives. Research by economists is extremely limited in this field, although the issue is relevant *per se* and for its policy implications. We address this niche by looking at some potential reasons that might explain the gap. In particular we focus on differential incentives that men and women face when they decide to commit a crime using the classical Becker's model of crime. We analyze property crimes primarily because earnings are a good measure of the expected benefits. Secondly in property crimes there is rarely a direct contact with a victim and thus gender endowments, that give a comparative advantage in some crimes like assault and prostitution (where respectively participation of males and females is favored) play a small role. Using novel micro data from the National Incident Based Reporting System, we document that females are responsible for 30% of the observed crimes, they earn, on average, 32 percent less than males and they face, on average, a 10 percentage points higher probability of arrest.

Once we account for the crime type, these differences disappear. In other words women choose those crimes where they have a comparative advantage and perceive to be at least as good as men. Considering the female pattern of offending, daylight crimes, such as shoplifting, that is the crime that women commit the most, are complements to everyday activity related to the household, consistent with previous findings in economic models of time use.

We also investigate whether women are more risk averse than men, as it is generally found in the legal market and we find that females sort into crimes with lower variation in the earnings risk.

The final part of this study investigates whether males and females, despite facing the same incentives, respond differently to them. We estimate a model for male and female participation in crime as a function of incentives (expected earnings and to the expected probability of not being arrested). We find that males respond to both incentives, while women respond to the expected earnings, with an elasticity that is only half as large as the one for men, but not to the probability of arrest. When we assign the male elasticities to the female cohort we find that, females could commit 40 percent more crimes and we can explain a little less than 50% of the participation gap.

2 Literature Review

Although criminologists, psychologists and sociologists have extensively written on women in crime, the subject is still highly under-investigated by economists. The early literature on female criminals (Lombroso & Ferraro, 1915; Freud, 1933) focuses on biological and psychological factors claiming that women who commit crimes have some masculine characteristics and that they are an anomaly.

Pollak (1961) concludes, in his pioneering book, that biological and psychological characteristics alone cannot explain the gender gap and that sociological factors play an important role. More recent literature on gender in crime has looked at the participation and arrest gaps (Steffensmeier, 1980; Steffensmeier & Allan, 1996) and has tried to explain female crimes using different theories: less biased police officers, targeting less serious typologies of crime, female emancipation, an increase in the economic marginalization of women, less social controls, more opportunities for female-type crimes, higher male incarceration rates and crime prevention programs targeted for males (Steffensmeier & Schwartz, 2003). In a similar vein, Weisheit (1984) cites a dominant hypothesis that female participation in crime would increase as social sex roles converge. However, in the last 15 years the broad social context has been redefining sex roles, yet, in the present study we find that female participation has stalled at 30 percent and the unconditional arrest gap seems to be constant for the same period[1], showing that while legal roles converge, the gaps in the unregulated criminal market remain. From a historical perspective, in the 70s concurrently with the women emancipation movements, there have been concerns about an increase in the female participation in crime[2]. In line with the zeitgeist, Simon (1976) discusses the trends in female criminal behavior. Using UCR data,

[1]The reader is referred to figures 1 and 9.

[2]See for e.g. Steffensmeier & Allan (1996) for a recent summary of trends in the gender gap in crime, as seen from the perspective of sociology.

she notes that female crime rates have increased two times from 1932 to 1972, measured by share of females in arrest rates, mostly property crimes. While "it is plausible to assume that policemen are becoming less "chivalrous" to women suspects", it alone cannot account for the increase in some types of crime instead of all of them. In this vein of thought, with our results we dispel the relevant myth that police officers might be lenient to female offenders. Cutting short through that, by exploiting data on reports and arrests, we show that females are no more less likely to be arrested than males, in present days. Even the opposite, they face a 1 percent higher probability of arrest, for any crime committed.

Another reason for lower female participation is that they might not get (or want to be) initiated into the crime culture like (or by) males because of stereotypes. The economic analysis of socially constructed identities was initiated by Akerlof & Kranton (2000). In their line of thinking, if crime was a masculine job then entering females would de-value the masculinity image and thus they would be ostracized by other males. While this would be equivalent to discrimination, it also illustrates that if females think that crime is non-feminine, they would be less likely to participate. This coincides with the opinion of Steffensmeier (1980) who notes that males are less likely to choose a female partner because they consider females to be less trustworthy and more governed by passions.

Interestingly, in an experimental setting both genders have similar propensities to break the law, as shown by Salmon & Serra (2013). They conduct an experiment that measures the effect of social judgment on rule breaking. While their experiment is tailored to measure the effect of cultural background on criminal type of behavior, they do not discuss gender differences and their variable for gender is rarely significant. If the two genders are similar when observed in a sterile setting, then probably it is the interplay of different environment factors that lead to a gap in participation, earnings and arrests.

As far as we know there are just three empirical studies by economists on women in crime. Here is a short description.

In an early economic study, Bartel (1979) investigates the determinants of female participation in crime through an Ehrlich type model of time division using U.S. data in 1970 in 33 different States. She uses the number of female arrests as the dependent variables and she finds that probabilities of conviction and arrest have a deterrent effect on females in some property crimes (burglary, robbery and auto-theft), but not in the crime that women commit the most, larceny. Although it is a very original and pioneering paper, the identification strategy, based on both OLS and 2SLS estimations, is not fully convincing in isolating the causal relationship between the independent variables and female arrests. The endogenous variable, the probability of apprehension and conviction, is instrumented using the expenditure on police protection and crime rate in the previous year, that are not exogenous with respect to the number of arrests in 1970. Furthermore she uses aggregate data and the same probability of arrests and conviction for men and women because she does not have data on people who have not been caught.

Gavrilova (2013) shows that females are discriminated against in the market of criminal partnerships because men decide to match with a woman to commit crime only if she is more productive than he is.

Corman, Dave and Reichman (2013) find that the 1996 welfare reform in the U.S., aimed at incentivizing female work, led to a decrease in female arrests for serious property crimes by $4.4 - 4.9\%$, while there was no significant effect on violent crimes.

Our paper gives a contribution to the scarce literature on women in crime by economists.

3 The model

We adopt the classical Becker's model on crime (Becker, 1968) where an individual compares the expected utility of committing a crime with the utility of not committing a crime. The expected utility of committing a crime is equal to the expected payoff that, in turn, is equal to the probability of not being apprehended $(1 - p)$ times the expected utility from earnings, U(Earnings), plus the probability of being apprehended (p) times the disutility of being arrested U(Jail). The utility of not committing a crime is equal to the wages from legitimate activities U(Wage). Then an individual decides to be involved in a criminal activity if equation 1 holds true:

$$E[U(Earnings)] * (1 - p) + U(Jail) * p > U(Wage) \tag{1}$$

In other words, if an individual is offered a wage in the legal market that is below his/her threshold wage (W^*), then he/she will decide to commit a crime:

$$W^* = U^{-1}\{E[U(Earnings)] * (1-p) + U(Jail) * p\} > Wage \tag{2}$$

The threshold wage W^* is a function of the expected utility of committing the crime that, in turn, depends on the expected earnings, the probability of arrest and the disutiliy of jail. While we do not have any measure of the disutility of jail, we do observe in our data the arrest outcomes and the earnings. Given the large gender participation gap we would expect a higher threshold wage W^* for men than for women and, consequently, large gender differences in the variables that determine the threshold. In the first part of our paper we test whether there are significant gender based differences in these variables, that represent the incentives to commit a crime, and that might explain part of the participation gap. The final part of this study investigates whether males and females, despite facing the same incentives, respond differently to them. In other words we investigate how small changes of the threshold wage W^* affect the decision to be involved in criminal activities.

4 Data

For our empirical analysis we use the National Incident Based Reporting System. This dataset records the universe of crimes for a given year for a given law-enforcement agency in the United States. It records demographic characteristics of perpetrators of reported crimes, the type of offense and arrest outcomes. This dataset is not representative for the United States, as many agencies do not submit reports and the expansion of data collection is on-going.

As already mentioned, we limit our analysis in the property crime market, where natural gender endowments should not give an advantage, as they do in crimes like prostitutions and assaults. We select the following UCR offense codes: 200 Arson, 231 Pocket-picking, 232

Purse-snatching, 233 Shop lifting, 234 Theft from Building, 235 Theft from Coin-Operated-Machine, 236 Theft from or of Motor Vehicle, 237 Parts, 238 All other larceny, 240 Motor Vehicle Theft, 220 Burglary, 120 Robbery, 280 Stolen Property Offenses. A typical observation is a coded report about a criminal incident. It contains the number of perpetrators, their demographic characteristics and crime codes, a victim report on how much was stolen and an arrest report, if an arrest has been effectuated. Criminal earnings are recorded no matter whether there was an arrest, and whenever there was a group crime (34 percent of the offenders commit a crime within a group) we have divided the earnings equally among the criminals.

Out of 10 million property crime observations over the period 1995 to 2010, 4 percent are perpetrated by criminals with unobserved race or gender. For our analysis we keep crime records for individuals between the ages of 15 to 65 years, an additional 8 percent of the sample are either too young or too old. For consistency[3] 12 more percent of the observations are dropped, leaving 8 million. A novelty of our analysis is that we know the criminal's earnings, as reported by the victim, and thus we drop a further 8 percent, where this variable is missing[4].

Table 1 shows the summary statistics. On average females are older than males, they are less likely to wield a weapon and to be part of gang. The average earning for females are 600$, while the male ones are 900$. Females have a higher arrest rate than males. Females are also less likely to commit a crime alone, hinting that they are not discriminated against in group entry and that there are no significant stereotypes to work with them. The last column shows the p-value of a 2 sided t test for difference in means, revealing that males and females are very different. Further tabulation of the data reveals that females seem to be narrowly specialized in crime, especially in burglary, shoplifting and theft from building. Looking at the number of observations, we record our first fact - in total, and in this subset of property crimes, females tend to commit 31% of all the offenses. In our empirical specifications we condition the estimates on agency-year specific trends. The size of these agency-year cells varies from 1 to 20 thousand crime reports, with a mean of 368 and a median of 135.

[3]Consistent are observations where in a given incident with for e.g. 3 criminals there are observations records for all 3 perpetrators. The initial data cleaning for unknown perpetrators might drop the record for the 3rd criminal in this example, leaving an incident of 3 criminals with 2 records. In this step, all such inconsistent observations are dropped.

[4]The deleted observations in this step are mainly incidents with burglary and stolen property offenses.

In the final part of our paper we generate a measure of crime and expectations over criminal proceeds and perceived likelihood of arrest. The crime measure is obtained by summing over individuals who share similar characteristics, such that they would face similar incentives. We define a group as a sum of criminal observations, defined over an interval of age (15-24, 25-34, 35-44, 45-54, equal or older than 55), race (Asian, Black, Indian and White) and gender (male, female). These groups form 40 cohorts, that vary over time and across 2605 local law-enforcement agencies. The resulting unbalanced panel of cohorts is treated as observations that can be tracked over time. We show the summary statistics in table 2. The log number of crimes for females for a group is 2.46, corresponding to approximately 12 crimes for women, and 3.25 for men correspondingly to approximately 26 crimes for men.

In figure 1 we plot the percentage of crimes committed by females. We observe that in the beginning of the sample period for every 3 male crimes there is 1 female and this ratio gradually falls to 2, so less crimes are committed by females than by males. In figure 9 we plot the ratio of arrests to crimes with respect to each gender and we observe that females face a higher arrest rate than males.

In figure 3 we plot the average value of total property stolen by a criminal from a given gender and age. As anticipated from the summary statistics, we observe a wage gap, where females earn on average 30 percent less than what males earn. Behind this average there might be significant heterogeneity hidden, so we explore the density of the obtained logged earnings in figure 4[5]. Females seem to concentrate their criminal efforts on earnings below 1000 USD, while males earn the slightly higher earningss. This might be due to the nature of the crimes in which males and females sort and the characteristics of their crimes.

One potential explanation for the different arrest rates could be differences in the monetary value of property stolen, the criminal "earnings". In figure 5 we mapped empirical probabilities of arrest to the percentiles of the earnings distribution for males and females. For the lower percentiles of the earnings distribution, males and females face similar arrest rates. As they diverge, females face higher arrest rates, while the earnings distributions follow a similar path until the median. After the 50th percentile male earnings are higher than female's and the arrest rates converge slightly. For the higher percentiles males earn more and face a higher

[5]The earnings distribution in nominal terms is presented in the next figure 5.

arrest rate. Overall, earnings and arrest rates do not seem to follow a specific pattern of co-movement. In figure 6 we plot the raw correlations between earnings and arrest risk for all crime types and we observe that they are close to 0. The average in the data is -0.06.

Given these unconditional patterns, in the next section we look at whether differences in the choice of crime attributes, such as weapon and being in a group, explain the gender crime gap.

5 Empirical Strategy

5.1 Patterns of Offending and Results

In this section we look at how attributes of crime contribute to the gaps in earnings and arrests between males and females. We estimate general specifications of the following kind:

$$Y_i = \beta_0 + \beta Female_i + X_i'\gamma + \delta_{offense} + \tau_{year \times agency} + \epsilon_i \tag{3}$$

where Y_i is the arrest and log transformed value of property stolen of criminal i[6]. X is a vector containing personal traits like race, age, weapon use and gang affiliation. A $\beta = 0$ would imply that there is no gender gap in any of these measures. In order to control for agency specific heterogeneity in any given year, we include agency-year fixed effects. Including offense fixed effects allows us to determine how much of the unconditional gap is due to differences between offenses. For example, we expect that a criminal would earn more in auto theft crimes than in shoplifting and if males specialize in the former, while females specialize in the latter, this would earn a high unconditional gap. Finally, we cluster the standard errors by level of reporting agency, in order to account for within time correlation in areas over which an agency has jurisdiction.

In table 4 we present results for the earnings gap. Each column presents estimates in which a new explanatory variable is added. In column 1 we see that the unconditional gap is 32 percent and it remains unchanged as we add in column 2 the different races in our sample. As

[6] Given that the log transformation would put more weight on the smaller values of earnings, in the appendix we present a table with raw earnings as dependent variable. The obvious drawback of this approach is that outliers would have more weight in the estimation. Given that earnings outliers are mostly the criminal work of males, the earnings gap would appear to be bigger.

we account for age in column 3 the gap starts to rise. Age attains a positive coefficient, which might be considered as evidence that older criminals select higher earnings opportunities.

In the following columns we add various attributes of criminal offending, interacted with the dummy for female. In column 4 we add the use of weapon. We see that if a male uses a weapon he gets lower earnings, than were he not to use one. In this column we test the conjecture that females with weapons might earn just as much as unarmed males, because a weapon would compensate for the lack of male intimidation. We find that females with weapons earn 30 percent less than males without weapons. This effect remains similar even when we account for offense type in the last column.

We add single offending in column 5 as a covariate. On average single male offenders earn more than group offenders and this effect does not seem to have a female specific dimension. In column 6 we add a gang dimension, and we find that females that are part of a gang earn less than other females. This effect remains roughly the same as we add more control variables. The gap drops to 30 percent as we account for year agency specific effects. As we add offense specific intercepts the average gap becomes zero. We interpret this as evidence that the gap is driven by between offense variations and, therefore, by sorting into different offenses. Looking at the covariates, we observe that the negative earnings gap persists among lone male and female offenders, gang members, while it is reversed for armed criminals and the excluded category of unarmed criminals offending in a group.

In table 5 we present the results for the arrest gap. In column 1 we observe that the unconditional arrest gap is 10 percent. In column 3 we control for offender age and we see that it is associated with a lower probability of arrest. This could be either due to older criminals being better at selecting safe targets, or, them being better at evading law-enforcement. In column 4 we add weapon as a criminal attribute and we see that it is associated with a lower probability of arrest. This could be due to successful intimidation to the victim, earning a non-conclusive description of the perpetrator. If females compensate with a weapon a lower capability for intimidation, then they could be compared again to the males without a gun and they indeed face a lower probability of apprehension.

Females that offend alone are less likely to get arrested than females who offend in a group, as can be seen from column 5. When we account for the between crime variation in the last 2 columns, we observe that single males are less likely to be arrested than single females. In column 6 we control for gang affiliation, which does not seem to be correlated to the probability of apprehension. Accounting for all these criminal attributes, leaves the average arrest gap at 9 percent. With the addition of year-agency fixed effects, the conditional gap decreases to 7 percent higher probability of arrest for females. In column 8 we add offense specific intercepts and we observe that the average arrest gap has diminished to 1 percent. This is further evidence that sorting into different offenses drives the unconditional arrest gap. However, we find that the arrest gap persists among single offenders.

Given that a lot of the criminal variation is explained by sorting into specific crimes, in table 6 we present an approach, borrowed from Bonin *et al.* (2007), that could allow us to uncover what role do risk-preferences have. In their contribution, Bonin *et al.* (2007) relate that "average willingness to take risk is higher in occupations that exhibit higher earnings risk". They generate the measure of earnings risk by taking the standard deviation of the residuals in a Mincerian wage regression. We do not observe the willingness to take risks, but we can observe in what occupations do females sort and, accepting the findings of Bonin *et al.* (2007), we want to claim the reverse: when a criminal sorts into a occupation with a high earnings risk, he has higher willingness to take risks. Finally, we want to determine whether endogenously females sort into offense types characterized with lower variation in the arrest or earnings, given that they are often found to be more risk-averse than males. The main issue with crime as an activity is the inherent risks associated with it. Women are consistently found to be more risk averse in experimental settings (see Croson & Gneezy (2009) and Eckel & Grossman (2008) for reviews) and in financial decision making (for e.g. Jianakoplos & Bernasek (1998)). Anderson & Mellor (2008) establish a negative correlation between risk aversion and risky behavior like cigarette smoking and heavy drinking, so arguably one can expect to find risk-loving women in crime. Bonin *et al.* (2007) show that individuals with lower willingness to take risk are more likely to sort into occupations with lower earnings risk. This begs the question how risky an activity like crime is and would not female participants sort into crime types, associated with lower risks. We build on this study by assuming that the opposite were also true: sorting patterns are sufficient to characterize risk aversion and willingness to take risks. Risk preferences can influence crime participation in 2 ways. First, through occupational sorting - females could sort into crime specializations that exhibit lower variance in the monetary value of property stolen. Second, risk-aversion could be implicated in the evaluation of the probability of apprehension. When a criminal considers the opportunity for committing a crime she might put a weight on the variance of the probability of arrest, especially if her criminal activities complement her household ones.

With this premises, we generate our dependent variable as the standard deviation of the residuals in an earnings and arrest regression by type of criminal offense. We did that by estimating a separate model for each offense, saturated with year-agency fixed effects[7]. Subsequently, in this model the dependent variable is constant within a given agency-year-offense cluster, therefore, we aggregated our dataset to this level by taking the means of the control variables. Given that we are mainly interested in the between crime variation within each agency, in our estimation we still account for agency-year effects[8].

In column 1 we observe that females sort into crimes with lower variation in the risk of arrest, as shown by the negative coefficient that the variable Female obtains. In column 3 we add the covariates and we see that this gap disappears. As we consider the earnings variation, we observe in column 4 that females sort into offenses with a lower variation in the earnings risk. As we add covariates in column 6 we observe that this holds true for non-armed criminals, offending in a group. Females operating alone seem also to sort into crimes with lower variation in the earnings with respect to males. The same holds also for female gang members, with there being no effect for armed females. Keeping the premises of the assumption that these results reveal risk preferences, we find that females are risk averse with respect to their earnings, but not with respect to arrest risk.

Exploring further the offense heterogeneity, in figure 10 we present graphically the coefficients on female by different crime types in a model in which the criminal attributes have not been interacted with gender. This allows us to plot a general measure of the gap, while the tables with the results can be found in the appendix. We observe that females earn more than males in crimes like shoplifting and motor vehicle theft. They earn less in robberies, burglaries and other different larceny offenses. There is no gender gap for pick pocketing,

[7]By doing so, we lose a few observation as in some markets the number of crimes reported is 1.

[8]Considering the identification of our model, we have 11 independent variables and 13 crimes that vary within each agency-year cell.

purse-snatching, theft from coin-operated machines and arson.

Similarly, in figure 11 we plot the coefficients for arrest risk for each separate crime. We see that females face a higher likelihood of arrest than males in robberies, shoplifting and purse-snatching. There is no arrest gap in pick pocketing, stolen property offenses and arson, while for all other larceny offenses the gap is in favor of females.

In summary, we find that unconditional gaps in earnings and arrest are partly driven by offense sorting. The average arrest gap is 1 percent, for any crime, while the one for earnings has disappeared. Females sort endogenously into crimes with lower variation in the earnings risk. Among the attributes of offending, armed females earn more than armed males and face a lower likelihood of arrest. Conditional on committing a crime alone, females earn less than males, sort into offenses with a lower variance in the earnings risk and face a higher likelihood of arrest. Conditional on gang affiliation, females earn less than males, face the same arrest risk and sort into occupation with a lower variance in the earnings risk.

In the next section, we explore the participation gap in crime. We look at whether males and females respond differently to the perceived incentives that affect their decision to take part in criminal activities and, if this is the case, how much of the gap in crime participation might be explained by these differences in elasticities.

5.2 The Role of Incentives

Broadly, the supply of crime depends on several factors: the legitimate labor opportunities of potential criminals, the probability of arrest and conviction, and the potential criminal earnings. The economic analyses typically assume that individuals respond to perceived incentives using all the available information. If the same is true for criminals, both the expected earnings and the expected probability of arrest should influence the decision to commit a crime. In this subsection we want to explore whether females and males respond differently to these two types of incentives. In order to do that, we develop a model for male and female participation to the crime market to estimate the elasticities of crime with respect to the expected earnings and to the expected probability not to be arrested. Let the expected utility of a criminal be:

$$E(U) = (1-p)\frac{L^{1-r}}{1-r} - pD > \varepsilon \tag{4}$$

where p is the probability not to be arrested, E are the earnings, r is the risk aversion coefficient, D is the disutility of jail.

Normalizing the disutility of jail time D to zero and assuming that ε is uniform (Durlauf *et al.*, 2010) one can sum over all individuals to obtain the total number of crimes committed, which are proportional to the expected earnings

$$C \propto (1-p)\frac{E^{1-r}}{1-r}, \tag{5}$$

Taking logs on both sides:

$$\log(C) = a + (1-r) * \log E + \log(1-p), \tag{6}$$

where a measures the size of the potential criminal population.

Our empirical model thus becomes:

$$\log(C_{gjt}) = \alpha_j + \beta_{1g}\log E_{jt-1} + \beta_{2g}\log(1-p_{jt-1}) + \beta_{3g}R_{jt} + \beta_{4g}Y_{jt} + \beta_{5g}A_{jt} + \varepsilon_{gjt} \tag{7}$$

where the subscripts $g \in \{f, m\}$, j and $t-1$ represent, respectively, females, males, the geographic location and the time period, while C is the number of crimes, α_j is location specific criminogenic effect (we will use different geographical levels), L is the earnings, conditional on not being arrested, $(1-p)$ is the probability of not being apprehended, R is a dummy for the race, Y is a dummy for the year, and ε are unobserved factors that influence crime. We use the lag for both the earnings and probability of not being arrested, assuming that criminals have adaptive expectations based on what happened in the previous year. This avoids potential simultaneity between the incentives and the decision to commit a crime. The equation is estimated using an OLS estimator. In all our estimates the standard errors are clustered at the agency level. Table 8 shows our estimates of the crime equation 7 using alternative specifications with and without location fixed effects. We observe that males respond to incentives in all the specifications: their decision to commit a crime positively depends on to the expected earnings and to the expected probability not to be arrested. The elasticity on the expected earnings is around 13% and is highly significant in all the specifications. The elasticity on the probability of not being arrested is around 40% and highly significant in all the specifications. As for females, elasticities are much lower in magnitude compared to those of males and they go in the expected direction only for earnings. The elasticity on expected earnings is positive in all the specifications, but significant just in two of them and is around half in magnitude compared to males. The elasticity on the probability of not being arrested is positive and significant at 5% just in the baseline equation (column 1) with a magnitude of 9%. In the specification with state fixed effects the coefficient is still positive, but not significant, while in last specification where we use county fixed effects, the coefficient is negative but barely significant and its magnitude is around 7%. To sum up, it seems that males respond to the incentives related to the decision to commit or not a crime (measured in terms of earnings and probability of not being apprehended). As for women, we find a response just for earnings, but not for the probability of arrest.

Next we use a Blinder-Oaxaca type decomposition technique to measure crime differentials between females and males that arise because females and males, on average, seem to respond differently to incentives. In other words, since we want to look at crime differentials between females and males, we construct a counterfactual equation for women where we replaced their coefficients on incentives with those from males's equation, or:

$$\log \widehat{C}^{CF}_{fjt} = \log \widehat{C}_{fjt} + (\widehat{\beta}_{1m} - \widehat{\beta}_{1f}) \log E_{jt-1} + (\widehat{\beta}_{2m} - \widehat{\beta}_{2f}) \log(1 - p_{jt-1}) \qquad (8)$$

Table 9 shows the value of the logarithm of crimes committed by women in the counterfactual scenario (row 1), the logarithm of crimes actually committed by women (row 2), and the logarithm of crimes actually committed by males (row 3). The average number of crimes committed by females in each cohort is 11.74, while for males it is 25.68. In the counterfactual scenario the number of crimes virtually (if they had the same elasticities as males for earnings and probability not to be arrested) committed by females would be 16.45, that is almost the 40% more than the number of crimes they actually commit. The counterfactual explains around 34 out of 79 log points difference between males and females.

Figure 7 shows the cumulative distribution function of the logarithm of crimes committed by females and by males. The female counterfactual cumulative distribution function is shifted towards the male one. Assuming that our incentive measures are correct and are the same for males and females, the remaining gap cannot be explained by differences in incentives.

6 Conclusion

In this article we reveal that gender gaps are not only a feature of the labor market, but also of the crime market. We contribute to the economics literature on crime by documenting gender patterns, a previously under-explored area. A further novelty of this paper, is that we account for criminal earnings. We identify unconditional participation, earnings and arrest gaps. We find evidence that crime sorting partly explains the average arrest and wage gaps. When we consider indirect evidence on risk preferences, we find that females endogenously sort into offenses with a lower variance in the earnings risk than males and they do not sort differently by variation in the arrest risk. We find that for any crime, females face a 1 percentage point higher probability of arrest, but earn the same as males on average.

Among the attributes of offending, armed females earn more than armed males and face a lower likelihood of arrest. Conditional on committing a crime alone, females earn less than males, sort into offenses with a lower variance in the earnings risk and face a higher likelihood of arrest. Conditional on gang affiliation, females earn less than males, face the same arrest risk and sort into occupation with a lower variance in the earnings risk.

To identify the possible motives for the gender gap in crime participation we look at how males and females respond to perceived incentives. Assuming that perceived incentives are measured correctly, we find that males' decision to engage in criminal activities depends on the expected earnings and on the probability of not being arrested, while females seem to respond only to the expected earnings and with an elasticity that is only half that of males. Such difference in the way the two genders respond to incentives explains almost half of the male-female participation gap in crime. Finally, we leave the resolution of the participation gap that we could not explain for future research.

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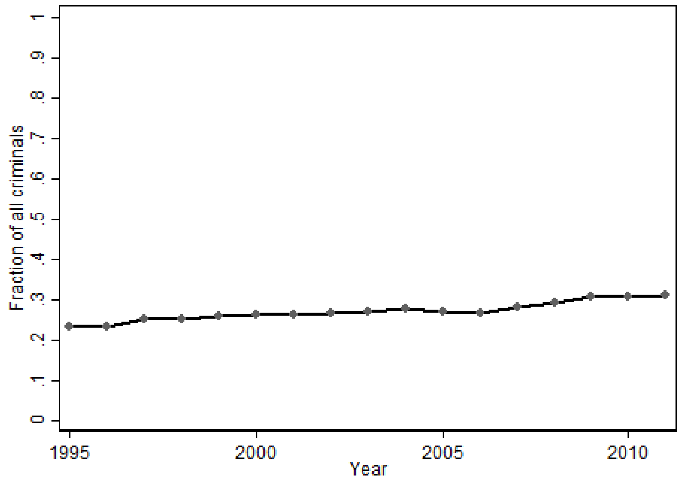

Figure 1: Participation Gap
Notes: In this graph the relative participation rate of females is plotted with respect to time. Each data point represents number of crimes committed by females with respect to all crimes.

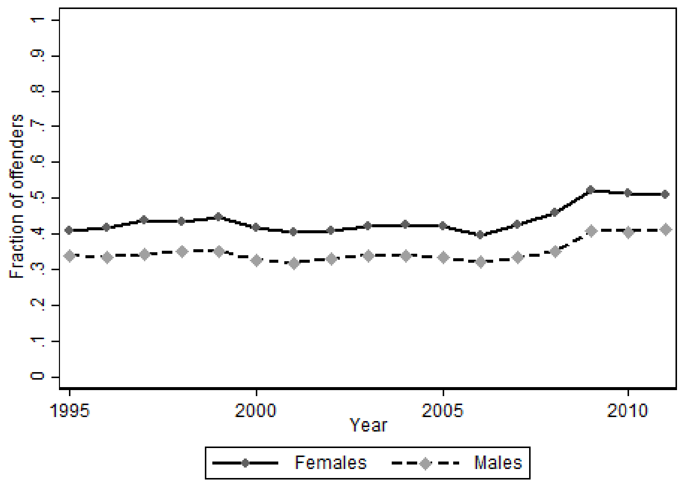

Figure 2: Arrest Gap
Notes: In this graph each line is the ratio of arrests with respect to crimes committed by the respective gender.

Figure 3: Earnings Gap

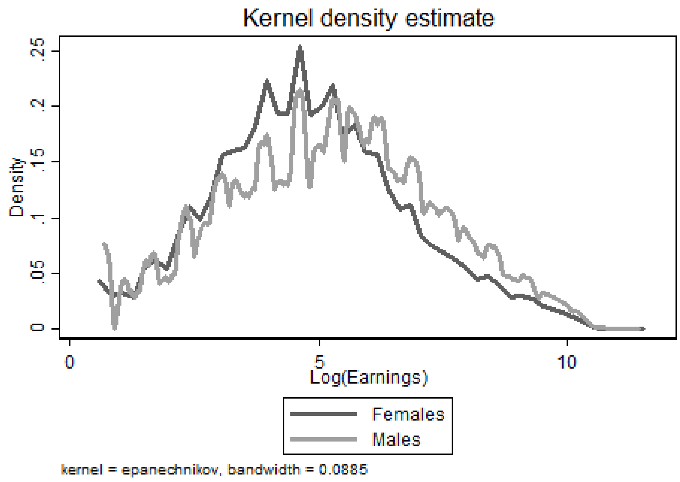

Figure 4: Densities of Logged Earnings by Gender

Notes: On this graph we plot the earnings distribution by gender. The spike after the 0 is due to recording practices, if the property stolen is not known, but positive it is recorded as 1USD.

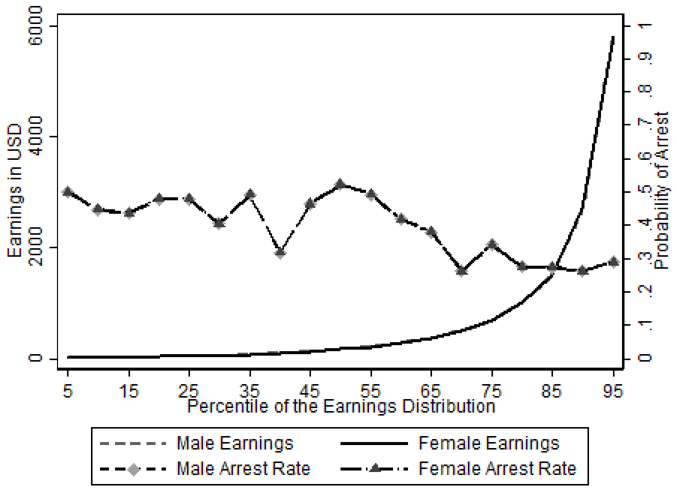

Figure 5: Relationship between Earnings and Arrest Probabilities
Notes: The horizontal axis depicts the percentiles of the earnings distribution. The left-hand vertical axis depicts the earnings in USD. The right-hand vertical axis depicts the probability of arrest. Each data point on the lines of the arrest rate is generated by taking the mean of the arrest realization for the respective percentile in the distribution of earnings.

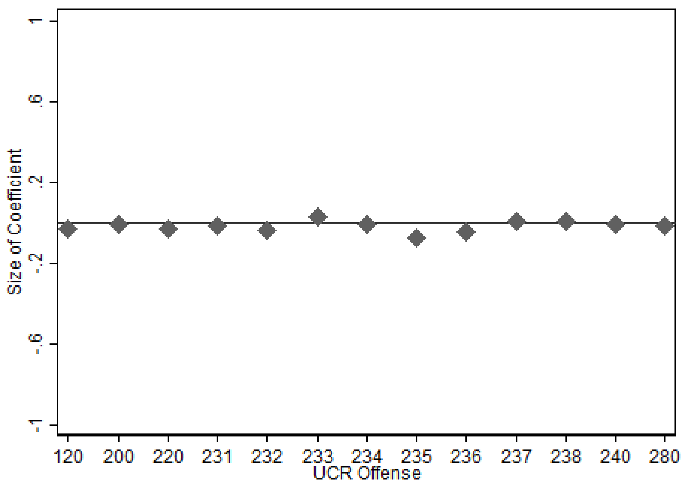

Figure 6: Coefficients of Correlation between Earnings and Arrest Rates by Crime Type
Notes: The horizontal axis shows the offense code for which the correlation coefficient has been estimated. The UCR offense codes are the following: 200 Arson, 231 Pocket-picking, 232 Purse-snatching, 233 Shop lifting, 234 Theft from Building, 235 Theft from Coin-Operated-Machine, 236 Theft from or of Motor Vehicle, 237 Parts, 238 All other larceny, 240 Motor Vehicle Theft, 220 Burglary, 120 Robbery, 280 Stolen Property Offenses.

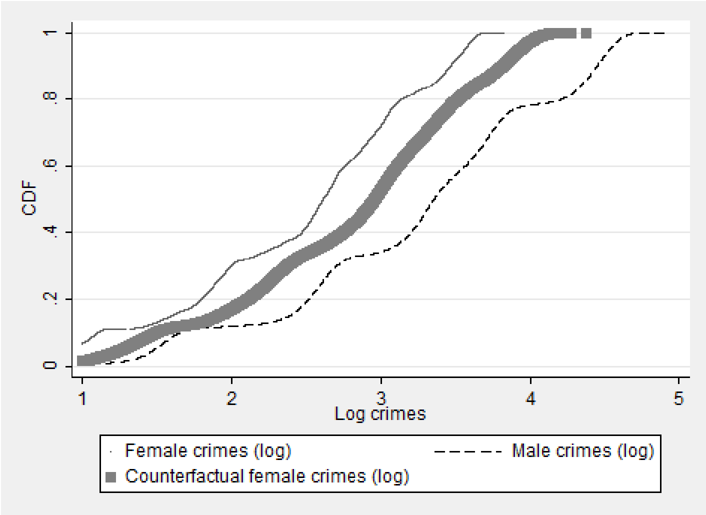

Figure 7: Crime Gaps in the counterfactual scenario
Notes: We plot the cumulative density function of crimes committed by males, females and by females in the counterfactual scenario.

Table 1: Summary Statistics for the period 1995-2010

	Mean	Female	Male	2 sided P-value
Age	28,199	28,738	27,989	0
Weapon	0,094	0,031	0,119	0
Gang	0,039	0,013	0,050	0
Whites	0,652	0,707	0,631	0
Asians	0,006	0,008	0,006	0
Indian	0,007	0,009	0,006	0
Earnings	1162,192	852,909	1290,238	0
Arrest	0,384	0,454	0,357	0
Alone	0,667	0,658	0,670	0
Offenses	1,119	1,092	1,130	0
231 Pocket-picking	0,002	0,003	0,002	0
232 Purse-snatching	0,003	0,003	0,004	0
233 Shoplifting	0,271	0,431	0,209	0
234 Theft from Building	0,088	0,107	0,081	0
235 Theft from Coin-Operated Machine	0,002	0,001	0,003	0
236 Theft from/of Motor Vehicle	0,054	0,025	0,065	0
237 Parts	0,013	0,005	0,016	0
238 All Other Larceny	0,244	0,263	0,236	0
240 Motor Vehicle Theft	0,063	0,043	0,071	0
220 Burglary	0,160	0,083	0,189	0
120 Robbery	0,074	0,020	0,095	0
280 Stolen Property Offenses	0,026	0,017	0,029	0
Observations	9400539	2630903	6769636	

The columns Female and Male denote the sample averages for females and males respectively in the rows. The last column shows the p-value of a t-test for difference in means between males and females.

Table 2: Summary Statistics for the Synthetic Panel

Variable	Obs	Mean	Std. Dev.	Min	Max
Log Crime (Female)	67272	2.46	1.24	0	7.49
Log Crime (Male)	67272	3.25	1.33	0	9.09
Log lag Earnings	67272	6.51	0.92	-0.53	9.51
Log lag Prob. of not being arrested	67272	-0.58	0.41	-5.36	0
Asian	67272	0.01	0.08	0	1
Black	67272	0.26	0.44	0	1
Indian	67272	0.01	0.09	0	1
Year	67272	2005.16	3.71	1996	2010
Age between 15 and 24	67272	0.23	0.42	0	1
Age between 25 and 34	67272	0.23	0.42	0	1
Age between 35 and 44	67272	0.23	0.42	0	1
Older than 54	67272	0.11	0.31	0	1

Notes: Excluded categories are *white* for the race, people in the *age between 45 and 54* and the *year 1996*

Table 3: Reconciling Crime Reports and Arrest Figures

	Crime	Females	Arrested	Females	Defendants	Females	Incarcerated	Females
Larceny	68 %	38 %	73 %	44 %	36 %	31 %	20 %	17 %
Burglary	17 %	15 %	14 %	12 %	37 %	11 %	60 %	5 %
Motor Vehicle	5 %	20 %	4 %	17 %	11 %	16 %	7 %	6 %
Others	11 %	12 %	10 %	16 %	15 %	17 %	13 %	1 %

Note: The second column shows what percentage of property crimes is classified according to the crime categories in the first column. The third column shows what percentage of these crimes were commited by females. The fourth column shows from all of the arrested how much were arrested for each crime category, with respectivelly how much of these arrests were females. The sixth and seventh column show hom much of all incarcerated were put behinf bars for each of the crime offenses and what percentage of that were females. All statistics pertain to the year 2010, except for defendants - 2009. Source: NIBRS, 2010, Department of Justice, 2012

Table 4: The Earnings Gap in Crime

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Earnings	Earnings	Earnings	Earnings	Earnings	Earnings	Earnings	Earnings
Female	-0.363***	-0.363***	-0.365***	-0.371***	-0.437***	-0.437***	-0.356***	0.179***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)	(0.012)	(0.008)
Age			0.003***	0.003***	0.008***	0.008***	0.006***	0.007***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Weapon				-0.018	-0.125***	-0.157***	-0.178***	-0.319***
				(0.028)	(0.025)	(0.036)	(0.038)	(0.020)
Female*Weapon				0.172***	0.192***	0.219***	0.154***	-0.140***
				(0.018)	(0.017)	(0.022)	(0.018)	(0.018)
Alone					-0.596***	-0.596***	-0.555***	-0.465***
					(0.014)	(0.014)	(0.013)	(0.007)
Female*Alone					0.068***	0.068***	0.038***	-0.142***
					(0.012)	(0.012)	(0.013)	(0.006)
Gang						0.081	-0.044	0.061
						(0.058)	(0.060)	(0.040)
Female*Gang						-0.068**	0.001	-0.104***
						(0.032)	(0.031)	(0.033)
Constant	5.236***	5.228***	5.148***	5.151***	5.416***	5.415***	5.434***	5.519***
	(0.020)	(0.029)	(0.040)	(0.038)	(0.039)	(0.039)	(0.024)	(0.028)
Observations	7,812,439	7,812,439	7,812,439	7,812,439	7,812,439	7,812,439	7,812,439	7,812,439
R-squared	0.006	0.007	0.007	0.007	0.024	0.024	0.096	0.356
Race controls	-	+	+	+	+	+	+	+
Year*Agency FE	-	-	-	-	-	-	+	+
Offense controls	-	-	-	-	-	-	-	+
Average Gap	-0.363***	-0.363***	-0.365***	-0.366***	-0.386***	-0.386***	-0.326***	0.080***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.008)	(0.006)

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 includes interacted year agency fixed effects and offense dummies where noted. The average gap is computed as the sum of all female variables, where the ones that are part of an interaction term were weighted by the female-specific mean in the respective criminal attribute.

Table 5: The Arrest Gap in Crime

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Arrest	Arrest	Arrest	Arrest	Arrest	Arrest	Arrest	Arrest
Female	0.097***	0.091***	0.093***	0.084***	0.093***	0.093***	0.064***	-0.017***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.004)
Age			-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.001***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Weapon				-0.107***	-0.111***	-0.101***	-0.087***	-0.028***
				(0.013)	(0.013)	(0.016)	(0.016)	(0.009)
Female*Weapon				0.019***	0.018***	0.022***	0.024***	0.060***
				(0.007)	(0.006)	(0.006)	(0.008)	(0.007)
Alone					-0.027***	-0.027***	-0.027***	-0.037***
					(0.006)	(0.006)	(0.006)	(0.005)
Female*Alone					-0.014***	-0.014***	-0.008**	0.032***
					(0.004)	(0.004)	(0.004)	(0.002)
Gang						-0.024	-0.015	-0.024
						(0.026)	(0.016)	(0.018)
Female*Gang						-0.012	-0.003	0.011
						(0.010)	(0.009)	(0.010)
Constant	0.357***	0.313***	0.373***	0.399***	0.410***	0.410***	0.426***	0.355***
	(0.008)	(0.011)	(0.016)	(0.013)	(0.014)	(0.014)	(0.007)	(0.015)
Observations	9,400,539	9,400,539	9,400,539	9,400,539	9,400,539	9,400,539	9,400,539	9,400,539
R-squared	0.008	0.013	0.015	0.019	0.020	0.020	0.147	0.256
Race controls	-	+	+	+	+	+	+	+
Year*Agency FE	-	-	-	-	-	-	+	+
Offense controls	-	-	-	-	-	-	-	+
Average Gap	0.097***	0.091***	0.093***	0.085***	0.084***	0.084***	0.059***	0.005**
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)

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 includes interacted year agency fixed effects and offense dummies where noted. The average gap is computed as the sum of all female variables, where the ones that are part of an interaction term were weighted by the female-specific mean in the respective criminal attribute.

Table 6: Results for the Gender Sorting in Crime

	(1)	(2)	(3)
	EarningsSD	EarningsSD	EarningsSD
Female	-0.070***	-0.048***	0.004***
	(0.005)	(0.003)	(0.001)
Age			0.000***
			(0.000)
Weapon			-0.001
			(0.009)
Female*Weapon			-0.015***
			(0.004)
Alone			0.014***
			(0.001)
Female*Alone			-0.008***
			(0.001)
Gang			0.018
			(0.027)
Female*Gang			-0.014
			(0.013)
Constant	1.772***	1.774***	1.704***
	(0.008)	(0.004)	(0.017)
Observations	139,404	139,404	9,205,070
R-squared	0.000	0.241	0.521
Race	-	-	+
Offense	-	-	+
Year*Agency FE	-	+	+

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 includes interacted year agency fixed effects and offense dummies. EarningsSD denote the standard deviation for the respective variable for each year-agency-offense code cluster.

Table 7: Robustness Checks for the Gender Gap in Crime

	(1)	(2)	(3)	(4)	(5)
	Arrest	Arrest	Arrest	Earnings	Earnings
Female	0.377***	0.236***	-0.006	0.135***	0.269***
	(0.021)	(0.013)	(0.004)	(0.007)	(0.009)
Age	-0.009***	-0.005***	-0.001***	0.007***	0.006***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Weapon	-0.475***	-0.288***	-0.039***	-0.255***	-0.155***
	(0.087)	(0.051)	(0.010)	(0.020)	(0.020)
Female*Weapon	0.147***	0.083***	0.057***	-0.158***	-0.203***
	(0.033)	(0.019)	(0.007)	(0.020)	(0.021)
Alone	-0.118***	-0.072***	-0.017***	-0.524***	-0.580***
	(0.024)	(0.015)	(0.005)	(0.008)	(0.008)
Female*Alone	-0.047***	-0.032***	0.025***	-0.125***	-0.120***
	(0.016)	(0.010)	(0.003)	(0.006)	(0.007)
Gang	-0.136	-0.078	-0.023	0.043	0.070
	(0.143)	(0.083)	(0.021)	(0.040)	(0.044)
Female*Gang	-0.022	-0.018	0.017	-0.116***	-0.105***
	(0.066)	(0.036)	(0.012)	(0.042)	(0.033)
Constant	-0.361***	-0.231***	0.376***	5.538***	6.085***
	(0.059)	(0.037)	(0.016)	(0.027)	(0.046)
Observations	9,400,539	9,400,539	6,297,342	5,359,041	3,076,665
R-squared			0.296	0.352	0.415
Race controls	+	+	+	+	+
Year*Agency FE	-	-	+	+	+
Offense controls	-	-	+	+	+
Estimation:	Logit	Probit			
Subsample:			Daylight	Daylight	Arrested

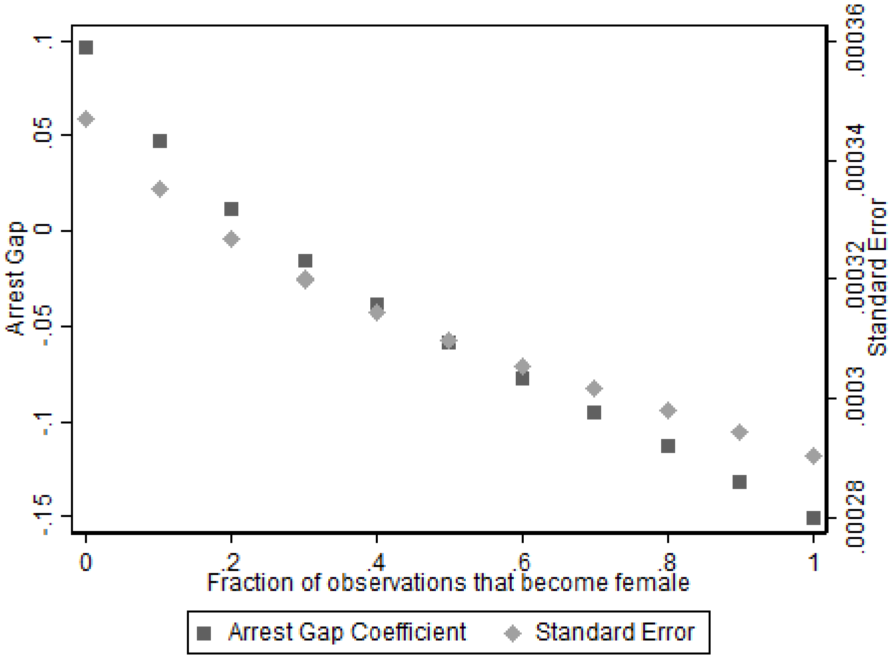

Figure 8: Arrest Gap Reporting Bootstrap

Notes: In this graph we present the arrest gap coefficient when different fractions of non-dayling non-arrest crimes have been assigned to be perpetrated by a female. Each of these observations was assigned a draw from a uniform distribution, in 15 replications, according to which for e.g. an observation with a draw .25 was on a male until the threshold fraction was less than .3, after which the perpetrator became female. The resulting arrest gap was plotted as a scatter point on this graph.

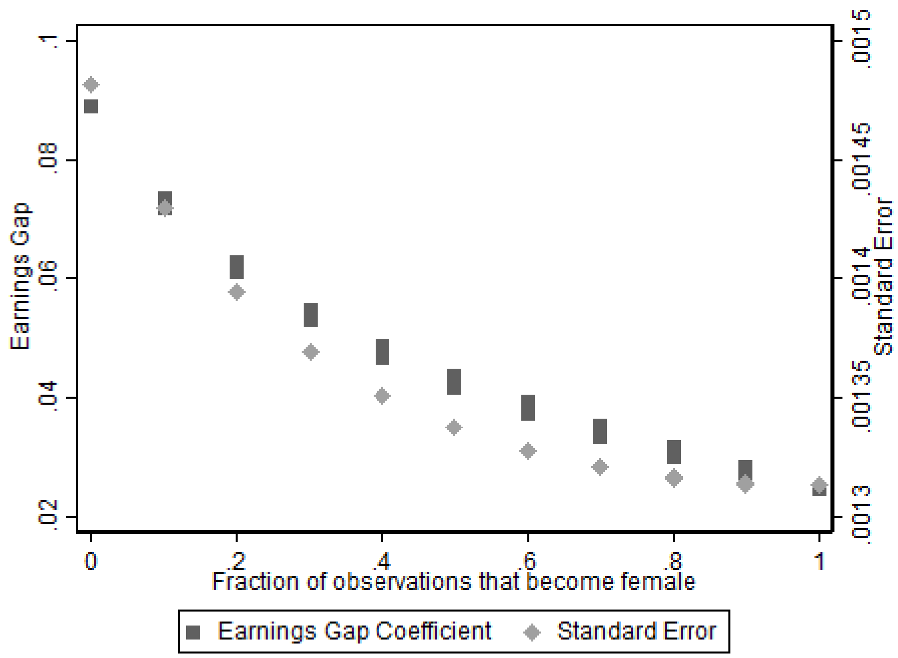

Figure 9: Earnings Gap Reporting Bootstrap

Notes: In this graph we present the earnings gap coefficient when different fractions of non-dayling non-arrest crimes have been assigned to be perpetrated by a female. Each of these observations was assigned a draw from a uniform distribution, in 15 replications, according to which for e.g. an observation with a draw .25 was on a male until the threshold fraction was less than .3, after which the perpetrator became female. The resulting earnings gap was plotted as a scatter point on this graph.

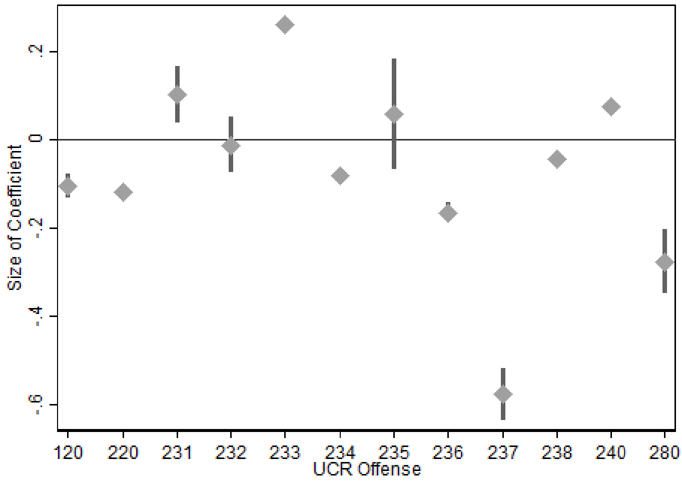

Figure 10: Coefficients on Earnings Regressions by Crime Type
Notes: In this graph the coefficients on the variable Female are depicted with 95 percent confidence intervals around them. Estimation includes interacted year agency fixed effects. The dependent variable is the logged transformation of the earnings. The horizontal axis shows the offense code for which the regression has been estimated. The UCR offense codes are the following: 200 Arson, 231 Pocket-picking, 232 Purse-snatching, 233 Shop lifting, 234 Theft from Building, 235 Theft from Coin-Operated-Machine, 236 Theft from or of Motor Vehicle, 237 Parts, 238 All other larceny, 240 Motor Vehicle Theft, 220 Burglary, 120 Robbery, 280 Stolen Property Offenses. The excluded category is black males. The non-significant result for Arson has been suppressed in order to magnify the confidence intervals for the other offenses. Regression tables can be found in the appendix.

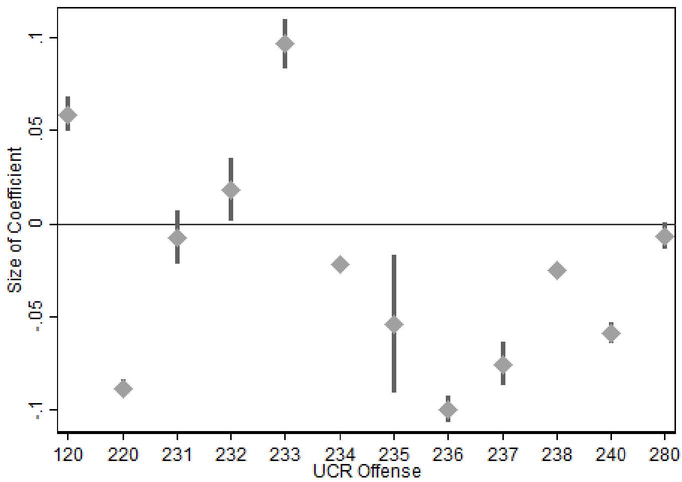

Figure 11: Coefficients on Arrest Regressions by Crime Type
Notes: In this graph the coefficients on the variable Female are depicted with 95 percent confidence intervals around them. Estimation includes interacted year agency fixed effects. The dependent variable is a dummy for arrest. The horizontal axis shows the offense code for which the regression has been estimated. The UCR offense codes are the following: 200 Arson, 231 Pocket-picking, 232 Purse-snatching, 233 Shop lifting, 234 Theft from Building, 235 Theft from Coin-Operated-Machine, 236 Theft from or of Motor Vehicle, 237 Parts, 238 All other larceny, 240 Motor Vehicle Theft, 220 Burglary, 120 Robbery, 280 Stolen Property Offenses. The excluded category is black males. The non-significant result for Arson has been suppressed in order to magnify the confidence intervals for the other offenses. Regression tables can be found in the appendix.

Table 8: Male and Female Crime Regressions

	Log Crime (Female)	Log Crime (Male)	Log Crime (Female)	Log Crime (Male)	Log Crime (Female)	Log Crime (Male)
	(1)	(2)	(3)	(4)	(5)	(6)
Log lag Earnings	0.058***	0.127***	0.0885***	0.166***	0.0351	0.125***
	(0.017)	(0.0204)	(0.0209)	(0.0243)	(0.0224)	(0.0215)
Log lag Prob. of not being arrested	0.090**	0.448***	0.0628	0.429***	-0.0786*	0.347***
	(0.041)	(0.0402)	(0.0480)	(0.0467)	(0.0476)	(0.0486)
Asian	-0.760***	-1.068***	-0.998***	-1.315***	-1.968***	-2.274***
	(0.107)	(0.115)	(0.130)	(0.126)	(0.191)	(0.227)
Black	-0.070*	0.184***	-0.0959**	0.136***	-0.336***	-0.0928**
	(0.040)	(0.0434)	(0.0404)	(0.0438)	(0.0390)	(0.0415)
Indian	-0.326**	-0.622***	-0.364**	-0.632***	-0.943***	-1.194***
	(0.147)	(0.145)	(0.175)	(0.168)	(0.181)	(0.166)
Age between 15 and 24	1.576***	1.835***	1.580***	1.841***	1.618***	1.876***
	(0.013)	(0.0139)	(0.0135)	(0.0140)	(0.0136)	(0.0139)
Age between 25 and 34	1.026***	1.090***	1.030***	1.095***	1.068***	1.130***
	(0.010)	(0.0108)	(0.00998)	(0.0109)	(0.00994)	(0.0108)
Age between 35 and 44	0.688***	0.684***	0.691***	0.689***	0.726***	0.721***
	(0.009)	(0.00858)	(0.00884)	(0.00855)	(0.00867)	(0.00816)
Older than 54	-0.687***	-0.848***	-0.710***	-0.878***	-0.889***	-1.054***
	(0.016)	(0.0199)	(0.0163)	(0.0197)	(0.0167)	(0.0184)
Constant	1.418***	2.013***	1.195***	1.750***	1.513***	2.016***
	(0.133)	(0.155)	(0.147)	(0.169)	(0.155)	(0.152)
State FE	no	no	yes	yes	no	no
County FE	no	no	no	no	yes	yes
Observations	67,272	67,272	67,272	67,272	67,272	67,272
R-squared	0.333	0.422	0.362	0.455	0.551	0.624

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Errors are clustered at the reporting agency level. We estimate the elasticities of the number of crimes committed with respect to the expected booty and to the expected probability to be arrested for both females and males.

Table 9: Crimes committed by females in a counterfactual scenario

Variable	Obs	Mean	Std. Dev.	Min	Max
Log Crime (Female) - Counterfactual	67272	2.80	0.81	-1.07	4.37
Log Crime (Female)	67272	2.46	1.24	0	7.49
Log Crime (Male)	67272	3.25	1.33	0	9.09

Notes: We construct a counterfactual equation using a Blinder-Oaxaca type decomposition technique to measure crime differentials between females and males that arise because females and males, on average, respond differently to incentives, measured in terms of expected loot and expected probability not to be arrested

A Raw Earnings Gap

B Disaggregated Crime Tables

Table A.1: The Earnings Gap for Different Crimes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Earnings	Earnings	Earnings	Earnings	Earnings	Earnings	Earnings	Earnings
Female	-437.329***	-439.072***	-443.196***	-463.423***	-641.632***	-641.578***	-539.520***	-101.019***
	(12.831)	(10.834)	(10.778)	(8.437)	(17.583)	(17.400)	(13.970)	(6.633)
Age			6.462***	6.157***	9.079***	9.079***	7.513***	9.354***
			(0.700)	(0.699)	(0.636)	(0.635)	(0.600)	(0.376)
Weapon				-204.910***	-279.547***	-343.815***	-380.465***	-343.570***
				(53.531)	(49.452)	(43.251)	(41.123)	(27.816)
Female*Weapon				201.875***	251.652***	305.465***	247.004***	-33.738
				(36.202)	(33.570)	(27.380)	(25.134)	(21.710)
Alone					-403.940***	-403.986***	-365.658***	-354.018***
					(20.340)	(20.133)	(15.618)	(9.245)
Female*Alone					250.126***	250.110***	208.528***	106.309***
					(18.961)	(18.747)	(15.312)	(8.527)
Gang						158.745	-9.479	108.483
						(143.972)	(51.431)	(66.784)
Female*Gang						-130.747	-16.435	-108.785**
						(82.153)	(32.950)	(51.667)
Constant	1,290.238***	1,270.083***	1,089.780***	1,136.813***	1,332.483***	1,331.199***	1,331.973***	2,006.625***
	(22.069)	(44.876)	(57.134)	(51.196)	(57.522)	(56.189)	(26.294)	(93.506)
Observations	7,812,439	7,812,439	7,812,439	7,812,439	7,812,439	7,812,439	7,812,439	7,812,439
R-squared	0.004	0.004	0.004	0.005	0.007	0.007	0.040	0.248
Race controls	-	+	+	+	+	+	+	+
Year*Agency FE	-	-	-	-	-	-	+	+
Offense controls	-	-	-	-	-	-	-	+
Average Gap	-437.329***	-439.072***	-443.196***	-457.77***	-469.253***	-469.141***	-394.947***	-32.89***
	(12.831)	(10.834)	(10.778)	(8.783)	(8.586)	(8.453)	(7.599)	(4.207)

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Errors clustered at the reporting agency level. Estimation includes interacted year agency fixed effects where noted. The dependent variable is the criminal earnings. The excluded category is black males.

Table B.1: The Earnings Gap for Different Crimes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
UCR Code:	231	232	233	234	235	236	237	238	240	220	120	280
Female	0.074	0.057	0.295***	-0.076***	0.017	-0.094***	-0.381***	-0.112***	0.054***	-0.065***	-0.017	-0.183***
	(0.076)	(0.040)	(0.010)	(0.013)	(0.067)	(0.017)	(0.044)	(0.010)	(0.013)	(0.010)	(0.108)	(0.046)
Age	0.001	-0.001	0.011***	0.009***	0.003	0.004***	-0.017***	0.008***	-0.002***	0.001**	0.005***	-0.001
	(0.002)	(0.002)	(0.001)	(0.000)	(0.004)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
Weapon	-0.172	-0.156*	0.057***	-0.649***	-0.649	-0.406***	-0.409***	-0.388***	-0.048**	-0.791***	-0.058	-0.191*
	(0.116)	(0.087)	(0.019)	(0.027)	(0.485)	(0.039)	(0.078)	(0.028)	(0.024)	(0.043)	(0.061)	(0.114)
Female*Weapon	-0.096	-0.060	0.099***	0.004	-1.209**	0.083	0.122	0.052*	-0.028	-0.153**	0.013	-0.034
	(0.251)	(0.191)	(0.025)	(0.047)	(0.533)	(0.090)	(0.202)	(0.027)	(0.061)	(0.071)	(0.107)	(0.218)
Alone	-0.137**	-0.146***	-0.735***	-0.394***	-0.233***	-0.253***	-0.514***	-0.496***	-0.042***	-0.339***	-0.259***	-0.254***
	(0.061)	(0.043)	(0.015)	(0.012)	(0.089)	(0.014)	(0.033)	(0.012)	(0.010)	(0.008)	(0.014)	(0.044)
Alone*Female	0.037	-0.111*	-0.057***	-0.009	0.117	-0.119***	-0.304***	0.089***	0.029**	-0.086***	-0.234***	-0.142**
	(0.086)	(0.062)	(0.011)	(0.014)	(0.143)	(0.021)	(0.050)	(0.011)	(0.013)	(0.013)	(0.021)	(0.055)
Gang	-0.010	-0.077	-0.014	-0.119*	0.479	-0.166***	-0.337***	-0.037	-0.038	-0.362***	0.190***	-0.208
	(0.173)	(0.136)	(0.028)	(0.061)	(0.486)	(0.054)	(0.118)	(0.028)	(0.038)	(0.056)	(0.042)	(0.165)
Gang*Female	0.126	0.355	-0.002	0.016	1.139	-0.119	0.226	-0.054	-0.063	0.121	-0.061***	-0.216
	(0.319)	(0.355)	(0.050)	(0.088)	(1.337)	(0.136)	(0.226)	(0.039)	(0.103)	(0.097)	(0.023)	(0.406)
Constant	4.739***	4.838***	4.053***	5.381***	4.162***	5.245***	5.969***	5.072***	8.263***	6.361***	5.206***	6.361***
	(0.067)	(0.048)	(0.022)	(0.019)	(0.137)	(0.021)	(0.056)	(0.016)	(0.016)	(0.018)	(0.066)	(0.059)
Observations	18,799	27,890	2,379,114	727,405	14,526	426,313	107,176	1,988,790	511,165	1,002,709	561,625	46,927
R-squared	0.392	0.399	0.205	0.164	0.587	0.165	0.342	0.142	0.205	0.167	0.100	0.378
Race	+	+	+	+	+	+	+	+	+	+	+	+
Year*Agency FE	+	+	+	+	+	+	+	+	+	+	+	+

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Errors clustered at the reporting agency level. Estimation includes interacted year agency fixed effects. The dependent variable is logged transformation of criminal earnings. The top of the column shows offense code for which the regression has been estimated. The UCR offense codes are the following: 200 Arson, 231 Pocket-picking, 232 Purse-snatching, 233 Shop lifting, 234 Theft from Building, 235 Theft from Coin-Operated-Machine, 236 Theft from or of Motor Vehicle, 237 Parts, 238 All other larceny, 240 Motor Vehicle Theft, 220 Burglary, 120 Robbery, 280 Stolen Property Offenses. The excluded category is black males.

Table B.2: The Arrest Gap for Different Crimes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
UCR Code	231	232	233	234	235	236	237	238	240	220	120	280
Female	-0.008	0.017	0.126***	-0.034***	-0.027	-0.094***	-0.088***	-0.046***	-0.057***	-0.078***	-0.026*	-0.014**
	(0.014)	(0.013)	(0.009)	(0.003)	(0.025)	(0.005)	(0.010)	(0.004)	(0.005)	(0.003)	(0.013)	(0.006)
Age	-0.001	0.001***	0.000	-0.002***	0.002	-0.002***	-0.002***	-0.001***	-0.005***	-0.001***	0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Weapon	0.010	0.028	-0.145***	0.029**	0.194**	0.076***	0.047**	-0.001	-0.007	0.026**	-0.583***	0.040***
	(0.030)	(0.037)	(0.015)	(0.012)	(0.079)	(0.017)	(0.021)	(0.008)	(0.011)	(0.012)	(0.017)	(0.007)
Female*Weapon	-0.029	0.088**	-0.017*	0.009	0.226	-0.024	-0.044	0.022***	0.060***	0.126***	0.076***	0.042**
	(0.050)	(0.041)	(0.010)	(0.014)	(0.226)	(0.019)	(0.046)	(0.007)	(0.018)	(0.010)	(0.016)	(0.017)
Alone	-0.011	-0.035**	0.105***	-0.002	-0.055**	-0.099***	-0.155***	-0.068***	-0.095***	-0.101***	0.000	-0.130***
	(0.012)	(0.016)	(0.008)	(0.004)	(0.024)	(0.006)	(0.012)	(0.004)	(0.010)	(0.005)	(0.005)	(0.008)
Alone*Female	0.001	-0.000	-0.046***	0.016***	-0.077**	-0.011*	0.019	0.027***	-0.004	-0.029***	0.022***	0.010
	(0.016)	(0.016)	(0.005)	(0.003)	(0.038)	(0.006)	(0.012)	(0.003)	(0.006)	(0.003)	(0.008)	(0.006)
Gang	0.057	-0.018	-0.069***	-0.037**	-0.284**	-0.129***	-0.111***	-0.023***	-0.036	-0.052**	-0.001	0.049***
	(0.063)	(0.042)	(0.020)	(0.018)	(0.126)	(0.018)	(0.027)	(0.009)	(0.028)	(0.021)	(0.011)	(0.015)
Gang*Female	0.009	-0.050	0.022	-0.004	-0.224	0.046*	0.088*	-0.004	0.033	-0.003	0.003	-0.026
	(0.089)	(0.071)	(0.017)	(0.021)	(0.238)	(0.026)	(0.053)	(0.008)	(0.028)	(0.013)	(0.008)	(0.035)
Constant	0.182***	0.170***	0.516***	0.298***	0.396***	0.411***	0.439***	0.325***	0.510***	0.428***	0.764***	0.468***
	(0.018)	(0.016)	(0.010)	(0.005)	(0.032)	(0.010)	(0.016)	(0.005)	(0.011)	(0.009)	(0.019)	(0.008)
Observations	22,136	31,448	2,550,052	826,944	20,163	505,610	122,548	2,290,006	595,207	1,501,105	693,858	241,462
R-squared	0.461	0.479	0.243	0.210	0.550	0.264	0.329	0.184	0.217	0.184	0.229	0.466
Race	+	+	+	+	+	+	+	+	+	+	+	+
Year*Agency FE	+	+	+	+	+	+	+	+	+	+	+	+

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Errors clustered at the reporting agency level. Estimation includes interacted year agency fixed effects. The dependent variable is a dummy for arrest. The top of the column shows offense code for which the regression has been estimated. The UCR offense codes are the following: 200 Arson, 231 Pocket-picking, 232 Purse-snatching, 233 Shop lifting, 234 Theft from Building, 235 Theft from Coin-Operated-Machine, 236 Theft from or of Motor Vehicle, 237 Parts, 238 All other larceny, 240 Motor Vehicle Theft, 220 Burglary, 120 Robbery, 280 Stolen Property Offenses. The excluded category is black males.