Uncovering the Gender Participation Gap in Crime

[preliminary and incomplete, please do not cite]

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October 2, 2016

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. 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. Starting from the classical Becker's model on crime we investigate some potential reasons for the participation gap looking at the differential incentives, measured in terms of earnings and probability of arrest. We observe that women obtain on average 32% less criminal earnings and face a 6% 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. 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. Females respond less to the monetary incentives and more to the non-monetary one (arrests). A Blinder-Oaxaca type decomposition technique shows that these difference can explain about one forth of the gender crime gap. We find that, in a counter factual scenario where the female incentives converge to the male ones increase to the level of the male ones, women would commit an additional 12% more crimes than they actually do.

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

Acknowledgements: We are grateful to Giovanni Mastrobuoni, Rodrigo R. Soares, Libor Dusek, Asaf Zussman, Michele Pellizzari, Olivier Marie and Mirko Draca for their useful comments. We also thank all the participants at the First Workshop on Culture and Institutions, Galatina, Italy; the First Conference on Empirical Legal Studies in Europe (CELSE), Amsterdam, Netherlands; the 30th Annual Conference of the European Society for Population Economics, Berlin, Germany; the Stockholm Criminology Symposium, Stockholm, Sweden; the Alpine Population Conference, Dondena Centre, Bocconi University, La Thuile, Italy; the Italian Society of Law and Economics - 10th Annual Conference, Roma, Italy; the XII Brucchi Luchino Labor Economics Workshop, Napoli, Italy; the 26th annual Conference of the European Association of Labor Economists, Ljubljana, Slovenia; the 13th Journes d'Economie Publique Louis-Andrè Grard-Varet, Aix-en-Provence, France; the Sixth Annual Meeting on the Economics of Risky Behaviors (IZA), Medellin, Colombia; the Scottish Economic Society Annual Conference, Perth, Scotland.

1 Introduction

Most of the evidence considered in the research on crime is focused on male perpetrators (Levitt & Miles, 2007; Freeman, 1999) with the implicit assumptions that female crime is so little that it is of no consequences or that policy implications have external validity across genders. Indeed, the number of women committing crime worldwide is much lower than that of men. But in recent time this gender gap is shrinking, making it a necessity to map out the differences in the criminal *modus operandi* of the two genders.

Figure 1 shows the trend in the percentage of women incarcerated over the the period 1930-2009 in the United States. The trend is clearly positive: the percentage of women incarcerated in 1930 was just 4.5% and it increased almost constantly[1] over the last 80 years, reaching 12% in 2009. The underlying participation in crime is even higher, as we will show later. This increasing trend mimics the decrease in the gender gap in the labor market. While there is an extensive literature on the legal gender gap, there is no research that looks at the gender gap in the crime market. Since the number of females committing crimes is on the rise, it is essential to understand how they differ from males in their criminal decision making in terms of opportunities, deterrents and violence.

In this article we attempt to tackle the difference between males and females by observing them in a ground neutral to relative gender endowments yet rich in economic incentives: property crime. We use micro data from the National Incident Based Reporting System for the period 1995 - 2011. We develop our analysis using the classical model of crime (Becker, 1968). An important advantage of the data are the availability of illegal earnings. We document that females are responsible for 30% of the observed crimes, where they earn, on average, 33 percent less than males and they face, on average, a 5 percentage points higher probability of arrest. Most notably, once we account

[1] The only exception is the post-Second World War drop that followed a peak in 1945 driven by the under representation of males due to wartime service.

for the crime type these differences disappear and even flip in favor of females. This hints that female criminals smartly self-select into crime types where they are expected to be on par with males.

The gender gap in the decision to engage in illegal activities might be driven on one side by biological factors, socio-cultural factors like the role of women in the household, among others. On the other side, it might be driven by factors captured by the Becker model such as opportunities in the legal labor market, economic returns to crime, deterrence and incapacitation. In our paper we focus on the latter factors in the form of incentives that alter the costs of engaging in criminal activities and thus shape the gender gap in crime. We develop a model where males and females face the same incentives but may respond differently to them. We use the model to solve for the participation decision in crime as a function of expected earnings and probability of arrest. We find that males are more responsive to the quantity of earnings, with an elasticity of 30.2 vs 27.4 for females, while females are more responsive to an increase in the probability of arrest, with an elasticity of 14.4 percent against 11.2 for males. By exploiting a partial Blinder-Oaxaca decomposition we find that if females were more "manly" with respect to incentives and responsiveness to them this would reduce the participation gap by 38 percent.

We contribute to several strands in the literature. Most prominently, 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 males and females. Since then there has been scant response to this apparent gap and we are the first to fully investigate this research question.

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.

An early economic study, Bartel (1979) investigates the determinants of female participation in crime through an Ehrlich type model of time division. She finds that probabilities of conviction and arrest have a deterrent effect on females in some property crimes. In contrast, in our study we find that females do not seem to respond to an increase in the probability of arrest but to the size of the earnings that they could attain. Recently, Corman, Dave and Reichman (2013) shed more light on the gender variation in crime. They 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 $4.4-4.9\%$. This figure is higher than the 3.5 percent we find for illegal earnings, hinting that females might respond more to the legal opportunity cost in crime than to the illegal earnings as identified in the present study. Finally, Gavrilova (2013) finds that females are likely discriminated against in the market for criminal partnerships, which might be one of the drivers for their lower participation.

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, she notes that female crime rates have increased two times from 1932 to 1972, measured by share of females in arrest rates, saying that "it is plausible to assume that policemen are becoming less "chivalrous" to women suspects". In this vein of thought, with our results we dispel the relevant myth that police officers might be lenient to female offenders.

Finally, by focusing our analysis on the earnings of criminals we are contributing

[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.

to the understanding of "the most understudied element of crime" (Draca & Machin, 2015). Recent literature has only attempted to approximate the earnings of criminals (Draca *et al.*, 2015), while we have more precise information on the value of the property stolen.

2 Data

We use the *National Incident Based Reporting System* (NIBRS). 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. 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.

As already mentioned, we limit our analysis in the property crime market, where we have a measure of illegal earnings and where natural gender endowments should not be as important as for crimes like prostitution and assaults. We use the following Uniform Crime Reporting (UCR) offense codes: 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, 261 Swindle, 262 Credit Card ATM Fraud, 263 Impersonation, 264 Welfare Fraud, 265 Wire Fraud, 250 Counterfeiting Forgery, 270 Embezzlement, 210 Extortion Blackmail, 510 Bribery.

Out of less than 39 million property crime observations over the period 1995 to 2011, 9.6 percent are perpetrated by criminals with unobserved gender[3]. For our analysis we keep crime records for individuals between the ages of 15 to 65 years, leaving us with 36 percent of the original sample. For consistency[4] 6 more percent of the observations are dropped, leaving 11 million.

Table 1 shows the summary statistics. The average earning for females are 960$, while the males are 1340$. Females face 9% higher probability of being arrested than males. On average females are older than males, they are less likely to wield a weapon and to be part of gang. 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. In our empirical specifications we condition the estimates on agency-year specific trends (agencies are law enforcement units that are smaller than counties). The size of these agency-year cells varies from 1 to 20 thousand crime reports, with a mean of 3 thousand and a median of 1109.

In figure 2 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 in total less crimes are committed by females than by males. In figure 3 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.

Except for one year, after an arrest we do not observe whether the arrestee is charged for a crime, or whether he eventually ends up in prison or not. Exploiting 2010 NIBRS data on reports and arrests, we show that females are no more less likely to be arrested than males, in present days. Even more, by performing a meta analysis on the way of

[3]For more details on the number of unknown offenders see Table A.3

[4]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.

females into the justice system we find that females are less likely to be defendants in court, and, if found guilty, less likely to get incarcerated. This can be observed in Table 2, where each column Females refers to the fraction of Females that first committed the crime, then got arrested, served as defendant and got incarcerated. We consistently observe that females fall out of the criminal justice system, as their relative fractions decrease at each step of the judicial process. With that in mind, our focus is going to be on the decision to engage in crime and on how such decision depends on the probability of arrest.

In figure 4 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 an illegal earnings 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 5[5]. Females seem to concentrate their criminal efforts on earnings below 1000 USD, while males earn the slightly higher earnings. 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 6 we map 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 arrest rate. Overall, earnings and arrest rates do not seem to follow a specific pattern of co-movement. In figure 7 we plot the raw correlations between earnings and arrest risk for all crime types and we

[5]The earnings distribution in nominal terms is presented in the next figure 6.

observe that they are close to 0. The average in the data is -0.06.

In the second part of the paper (see Section 5), where we investigate whether females and males respond differently to incentives, we construct crime rates using data on population by age, gender, race, year, and county from the Wide-ranging OnLine Data for Epidemiologic Research (WONDER). In those regressions we also control for average wages and employment rates by age, gender, race, decade, and state taken from the CENSUS Integrated Public Use Microdata Series (IPUMS-USA).

3 Model of Crime

In this section we develop the model of crime participation and the empirical specifications with which we can map the differences between the two genders in committing crime. We adopt a generalized Beckerian model of crime, where an individual compares the expected utility of committing a crime with the expected utility of not committing a crime. The expected benefits of committing a crime are the illegal earnings while the expected costs are the probability of arrest and the opportunity costs of being engaged in the labor market (wage, employment rate).

An individual decides to be involved in a criminal activity if a generalized function of costs and benefits is larger than an individual idiosyncratic error Υ^G, which measures any unobserved determinants of crime (sanctions, family reasons, etc.):

$$f^G(\widehat{Y}^G, \widehat{P}^G, \widehat{WAGES}^G, \widehat{EMPLOYMENT}^G) > \Upsilon^G \quad , \tag{1}$$

where:

$\widehat{Y}^G$ are expected economic returns to crime (criminal earnings)

$\widehat{P}^G$ is expected probability of arrest

In order to derive an estimable equation we do two things. First we aggregate the equation across individuals, deriving crime rates, then, since the function $f()$ is unknown, we log-linearize $f()$ with respect to all the incentives variables (small letters for logs):

$$cr^G = \beta_1^G \widehat{y}^G + \beta_2^G \widehat{p}^G + \beta_3^G \widehat{wages}^G + \beta_4^G \widehat{employment}^G + \varepsilon^G \tag{2}$$

The equation shows that the gender crime gap could be do to differences in incentives as well as differences in the way criminals of different gender respond to such incentives. In the next section we start by analyzing whether the incentives differ across gender, while in Section 5 we estimate Eq. 2 to estimate the elasticities.

4 Differences in incentives

In table 1 we document significant differences in term of incentives to commit crimes between males and females. Figures 3 and 4 show that these differences are persistent over time. To be sure that these differences in incentives are not driven by omitted factors (modus operandi, race, age, location, etc.) that are also correlated with gender we estimate the following specification:

$$Z_i = \beta_0 + \beta_1 FEM_i + X_i'\beta_2 + X_i \times FEM_i'\beta_3 + \delta_{offense} + \tau_{year \times agency} + \epsilon_i \tag{3}$$

where Z_i is either the arrest dummy or the 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 $\beta_1 = 0$ would imply that for the baseline that there is no gender gap in any of these measures. A $\beta_3 = 0$ would imply that for all female subgroups (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.

defined by the interaction) there is no gender gap.

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 correlation within areas (and over time) over which an agency has jurisdiction.

In table 3 we present results for the illegal earnings gap. Each column presents estimates in which a new explanatory variable is added. In column 1 we see that the unconditional gap is 30 percent and it remains unchanged as we account (column 2) for the different races and as we add age in column 3. 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 and 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 20 percent less than males without weapons, meaning that females manage to shrink the earnings gap through the use of a weapon.

We add single offending in column 5 as a covariate. On average single male offenders earn less than group offenders and seems that single females earn up to 11 percent more than single males. 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 earnings gap drops to 27 percent as we account for year agency specific effects. As we add offense specific intercepts the average gap flips sign and becomes 5 percent in favor of females. 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 4 we present the results for the arrest gap. In column 1 we observe that the unconditional arrest gap is 5 percent. It remains consistently close 5 as we account for more sources of differences between genders in the following columns. 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 5 percent. With the addition of year-agency fixed effects, the conditional gap decreases to 5 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 zero, meaning that sorting into different offenses drives the unconditional arrest gap. However, we find that the arrest gap persists among single offenders.

Exploring further the offense heterogeneity, in figure 8 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, motor vehicle theft and impersonation. They earn less in crimes such as robberies, swindling, and others. For crimes such as extortion or purse snatching there is no gender gap.

Similarly, in figure 9 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 and shoplifting. There is no arrest gap in pick pocketing, purse snatching, swindling, welfare fraud and others. The gap is in favor of females for thefts, burglaries, impersonation and forgery.

5 Responsiveness to incentives

5.1 Identification Strategy

We just saw that there are differences in incentives for men and women, as long as one does not look within crime categories. Such a selection might explain a large part of the observed gender crime gap. On top of this, men and women might respond differently to these incentives. Since we cannot estimate a discrete choice model of crime as we only have information on crimes committed (and not on individuals who decided not to commit crimes), to get a measure of crime that varies across "pseudo-individuals" we aggregate crimes within "cohorts" and divide by the corresponding population, thus getting a measure of crime rates (see Deaton, 1985).

Cohorts share similar characteristics such that they would face similar incentives to commit crimes and having similar expectations over criminal proceeds and perceived likelihood of arrest. They are defined based on: interval of age (15-24, 25-34 and 35-

44[7]), race (black and white), gender (male, female), and county. There are 17,388 cohorts for a total of 16 years (about 300,000 observations).

The resulting unbalanced panel is treated as pseudo-individuals that can be tracked over time, allowing for a large variety of fixed effects. For some cohorts, mainly those with few observations, we sometimes get estimated probabilities of arrest that are 0 or 1, or expected illegal earnings that are equal to 0. Since these are the product of cohorts of small size rather than their true expected values, we aggregate them sequentially over age group and then race, year, county, and finally typology of crime until we get values that are away from 0 or 1.

Given that we want to explore how the participation decision hinges on the two types of incentives, earnings and arrest, starting from Eq. 2 we obtain:

$$cr_{it} = \alpha_{ct} + \beta_1 \widehat{y}_{it} + \beta_2 \widehat{p}_{it} + x'_{it}\gamma + \delta_{offense} + \varepsilon_{it} \quad \text{for } G_{it} = m, f \tag{4}$$

where the subscripts i, c and t represent, respectively, the cohort, the county and the time period. cr is the log crime rate (the number of crimes committed in a given year by people of each cohort, defined by gender, age group, race, and county, divided by the general population in the same cohort), α_{ct} is the year by county fixed effect that capture factors that are common within a county for a given year (i.e. police presence), $\widehat{y}$ is the log of illegal earnings, $\widehat{p}$ is the probability of being apprehended, x is a vector containing personal traits (wage and salary income, employment rate, black race[8], age groups[9], $\delta_{offense}$ are typology of offense fixed effects. Finally ε_{it} are the idiosyncratic errors.

Using the contemporaneous values $\widehat{y}_{i,t}$ and $\widehat{p}_{i,t}$ we face two potential issues i) reverse

[7]Data on the general population at county level are just available till the age of 44 and we know that most of the crimes are committed by young people.

[8]The excluded category is white.

[9]Age group 35-44 is the excluded category.

causality due to the potential simultaneity between the incentives and the decision to commit a crime (for example, crime congestion might lower the likelihood of apprehension) and ii) due to the yearly aggregation criminals' expectations might be based on future crimes, introducing additional measurement error.

A simple fix would be to use the lagged values of the incentives, which implicitly assumes that the proper expectations of criminals are adaptive, being based on what happened in the previous year. Since it might be the case that $z_{i,t-1} = (y_{i,t-1}, p_{i,t-1})$ are not the true criminals' expectations, we face potential measurement error. Rather than relying on such an assumption, we model the expectations for both illegal earnings and probability of arrest and test whether they are adaptive (ρ=1).

$$z_{it} = \delta_{ct} + \rho z_{i,t-1} + X'_{it}\eta + \theta_{offense} + \xi_{it} \text{ for } G_{it} = m, f \tag{5}$$

Modelling the expectations we can use a two step procedure, where in the first stage we obtain $\widehat{p}$ and $\widehat{y}$ and in the second step these measures are plugged into equation 4. In other words, these equations turn out to be a first stage in a 2SLS setup where y_{t-1} and p_{t-1} are used as instruments for y_t and p_t.

The results of all these steps are shown in section 5.3.

5.2 Blinder-Oaxaca decomposition

In order to gauge the importance of the elasticities in determining the gender crime gap we use a partial Blinder-Oaxaca decomposition (limited to p and y). The decomposition measure the fraction of the gender crime gap that arises because: i) females and males, on average, respond differently to incentives and ii) face different incentives.

The counterfactual equation for women where we replace their coefficients on incentives with those from the male equation is:

$$\widehat{cr}_{fit}^{CF,\beta s} = \widehat{cr}_{fit} + (\widehat{\beta}^z_m - \widehat{\beta}^z_f) z^f_{it} \tag{6}$$

The counterfactual equation for women where we replaced their incentives (their "endowment') with those from male equation is:

$$\widehat{cr}_{fit}^{CF,Xs} = \widehat{cr}_{fit} + (z^m_{it} - z^f_{it}) \widehat{\beta}^z_f \tag{7}$$

It can be shown the fraction of the crime gap that can be explained by differences in incentives and elasticities is

$$fraction \;\; explained \;\; = \;\; \frac{\widehat{cr}_{fit}^{CF,\beta s} - \widehat{cr}_{fit}}{\widehat{cr}_{mit} - \widehat{cr}_{fit}} + \frac{\widehat{cr}_{fit}^{CF,Xs} - \widehat{cr}_{fit}}{\widehat{cr}_{mit} - \widehat{cr}_{fit}} \tag{8}$$

When using all Xs and all βs this fraction becomes 1.

5.3 Results

Table 5 shows our estimates of the first stage and of the reduced form using alternative specifications with and without county fixed effects and their interaction with year fixed effects. The lag of the (log) probability of arrest and the lag of (log) illegal earnings are good predictors of, respectively, the probability of arrest and illegal earnings. The F-statistics is, in all the specifications, well above the rule of thumb of 10. Since the αs in both the equations are lower than 1, it follows that expectations are not adaptive.

In line with the first stage the results, the reduced form cannot be interpret as the true elasticities but it is reassuring that the coefficients have the right sign (larger risks of arrest lower crime while larger illegal proceeds increase crime) and are statistically significant at the 1 percent level. In Table 6 we use these results to get the two stage least squares elasticities. All elasticities are highly significant, and important in magnitude. The coefficient on illegal earnings for males is equal to 11 when we do not control for county fixed effects. Once we do control for such fixed effects the elasticity jumps to about 30%. Similar jumps are observed for females, 5.8 and 28%, who tend to always respond less to criminal earnings (the difference is statistically different from zero). Adding county fixed effects appears to control for important omitted variables. The most natural that come to mind is police presence, which is typically organized around counties. One possible explanation for the jump is that police forces are more likely to protect rich neighborhoods, which is where criminal proceeds tend to be larger. Interacting county fixed effects times year fixed effects changes the coefficients very little.

Controlling for county fixed effects the elasticity with respect to the probability of arrest is -12.5% for males -16.2% for females (the difference is statistically different from zero), indicating that women respond more to the risk of apprehension.

As for the other variables, young people and black people are more likely to commit crimes. The coefficients on employment rate and on wage and salary income change in the different specifications that we use. These results seem to be highly dependent on the inclusion of the fixed effects. When we use the fixed effects the employment rate is negatively associated, as expected, to the crime rates, while income is positively associated to crime rates (it might be explained thinking that income reflects the presence of individuals who provide good targets for criminals involved in property crimes).

Consistent with the measurement error problems outlined before, the OLS estimates shown in Table 7 are much smaller in magnitude and sometimes fail to be significantly different from 0. To sum up, when modelling the expectations in a proper way both male and female criminals respond to incentives, though, compared to men, women tend to respond less to monetary incentives and more to non-monetary ones.

In Table 8 we perform some robustness checks to be sure that our results do not depend on the particular specification we used. First of all, instead of discarding data with missing values for illegal earnings, we assign them the average of illegal earnings that we compute aggregating over age group and then race, year, county, and finally typology of crime until we get values that are different from 0. The differences between men and women stay the same, though the elasticities with respect to illegal earnings tend to be smaller in absolute value while those with respect to the probability of arrest tend to be larger (in absolute value).

To be sure that our results are not biased by the different dimension of the counties, we estimate a weighted regression, weighting for population (this does very little to our estimates). As a third robustness check we run a regression controlling for other two characteristics of criminals: whether they commit a crime alone and whether they use a weapon, again with almost no changes in the elasticities. Finally we use the number of crimes instead of the crime rates as our dependent variable. Again, our estimates are in line with our main results. Both men and women respond to incentives in the expected directions: the coefficient on expected illegal earnings is positive and significant while that on the expected probability of arrest is negative and significant.

How much can these differences in the elasticities explain the crime gap? Using Eq. 8 the fact that women respond more to the arrest probabilities and less to the monetary incentives explains 26% of the gap. Another 12 percent is due to the differences in incentives men and women face. The counterfactual CDFs of female crime if they responded to the incentives like men are shown in Figure 10, while Figure 11 shows what would happen if they faced the same incentives.

6 Conclusion

In this article we reveal that gender gaps are not only a feature of the labor market. Women and considerably less likely to engage e in crime. We contribute to the economic 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.

To identify the possible motives for the gender gap in crime participation we look at how males and females respond to perceived incentives. We find that both men and women decision to engage in criminal activities depends on the expected earnings and on the probability of being arrested. Men are significantly more responsive than women to the expected illegal earnings, while women respond more in terms of responsiveness to the expected probability of arrest. Such difference in the way the two genders respond to incentives explains one-fourth 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: Women Incarcerated out of all US Criminals

Sources: National Archive of Criminal Justice Data. Online at https://www.icpsr.umich.edu/icpsrweb/NACJD; U.S. Census Bureau, Statistical Abstract of the United States: 2011, Law Enforcement, Courts and Prisons.

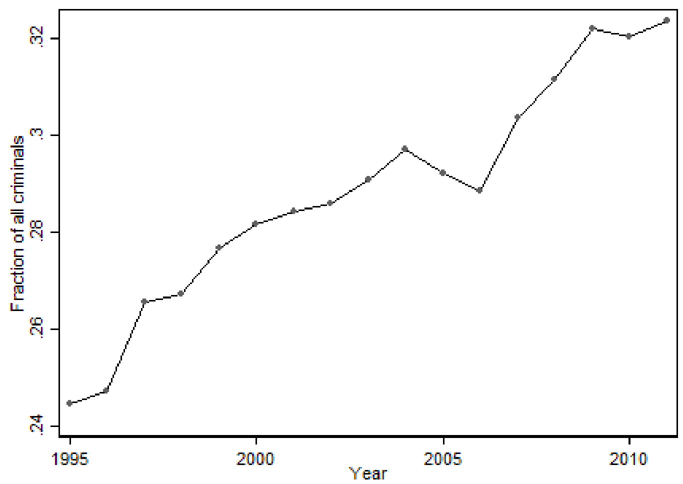

Figure 2: Participation Gap

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.

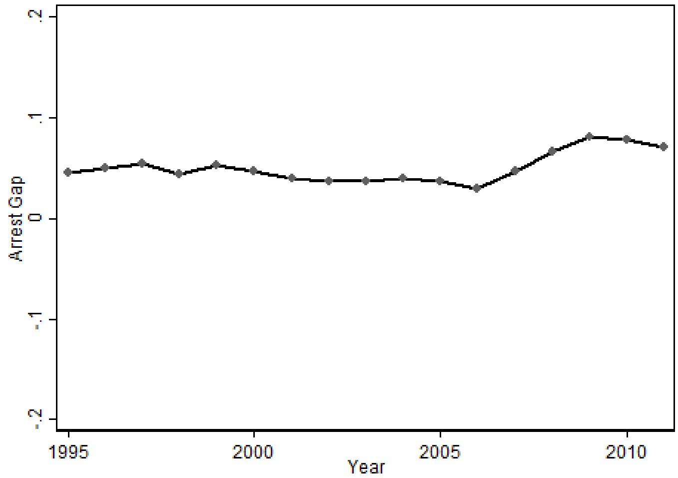

Figure 3: Arrest Gap

Notes: Female - Male arrest probabilities.

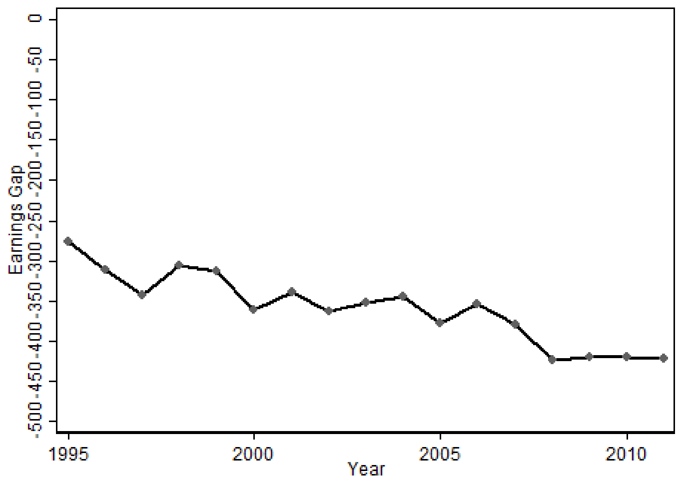

Figure 4: Illegal Earnings Gap

Notes: Female - Male average illegal earnings.

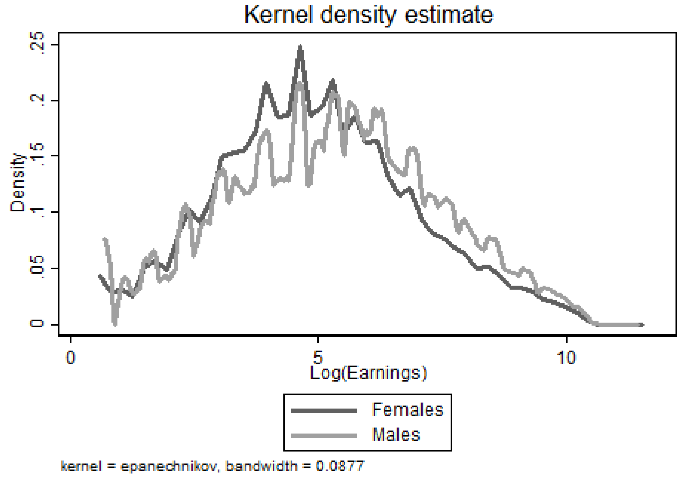

Figure 5: Densities of Logged Earnings by Gender

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.

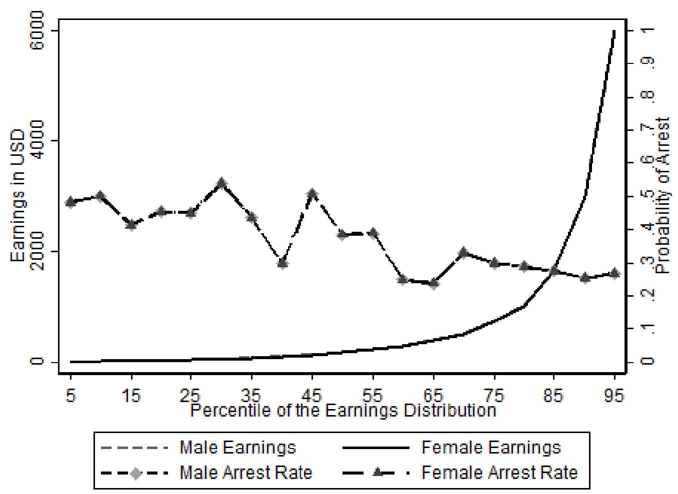

Figure 6: Relationship between Earnings and Arrest Probabilities

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.

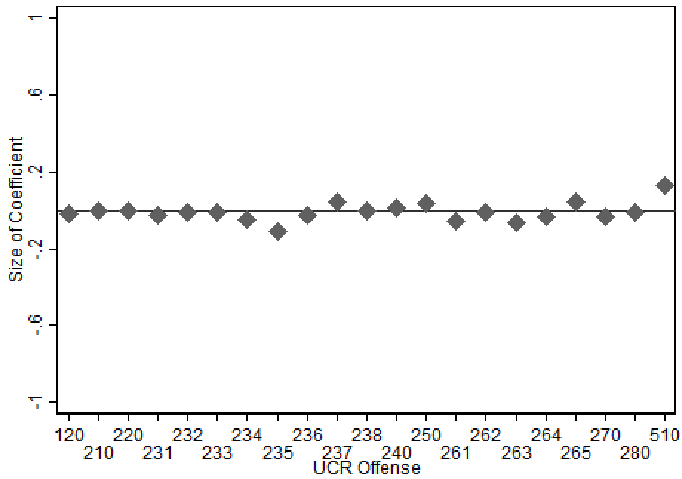

Figure 7: Coefficients of Correlation between Earnings and Arrest Rates by Crime Type

Notes: The horizontal axis shows the offense code for which the correlation coefficient has been estimated. The UCR offense codes are the following: 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.

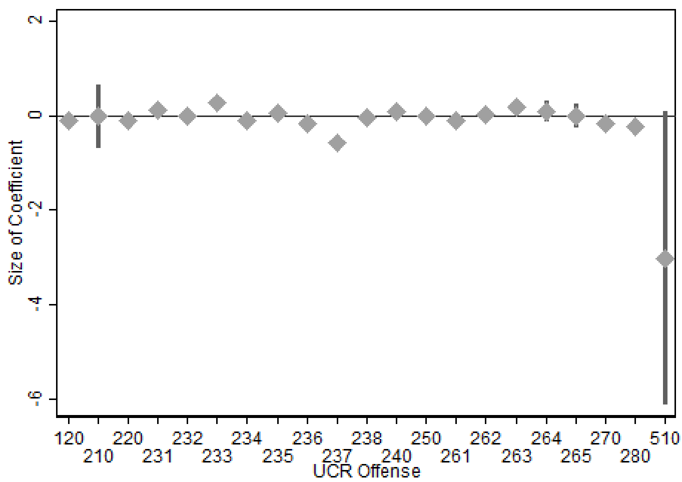

Figure 8: Coefficients on Earnings Regressions by Crime Type

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.

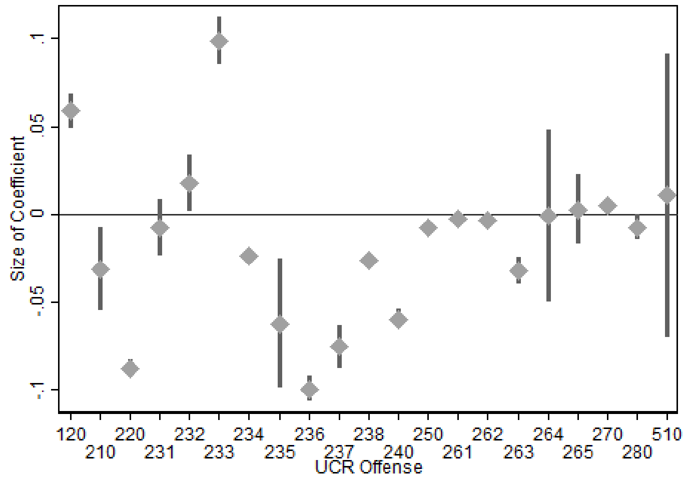

Figure 9: Coefficients on Arrest Regressions by Crime Type

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.

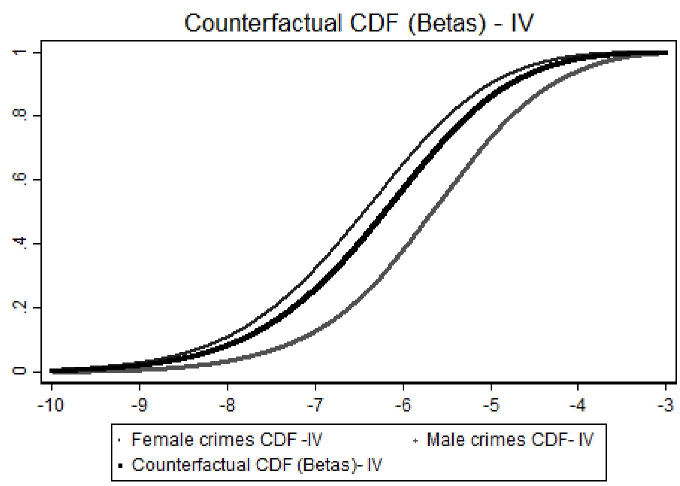

Figure 10: Crime Gaps in the counterfactual scenario

Notes: We plot the male, female and female counterfactual scenario (with the male coefficients) cumulative density function of crime rates.

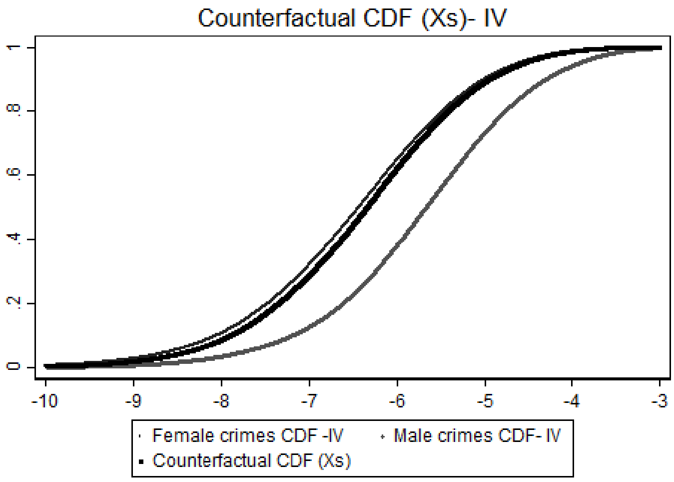

Figure 11: Crime Gaps in the counterfactual scenario

Notes: We plot the male, female and female counterfactual (with the male endowments) cumulative density function of crime rates.

Table 1: Summary Statistics for the period 1995-2010

	Males	Females	Total	P-value
Illegal Earnings	1340.9	962.3	1225.9	0
	(3505.9)	(2930.2)	(3346.1)	
Arrest	0.341	0.429	0.367	0
	(0.474)	(0.495)	(0.482)	
Age	28.20	28.87	28.41	0
	(11.01)	(10.99)	(11.01)	
Weapon	0.104	0.0274	0.0810	0
	(0.306)	(0.163)	(0.273)	
Gang	0.0432	0.0110	0.0334	0
	(0.210)	(0.107)	(0.186)	
White	0.642	0.707	0.661	0
	(0.480)	(0.455)	(0.473)	
Asian	0.00591	0.00773	0.00647	0
	(0.0767)	(0.0876)	(0.0802)	
Indian	0.00575	0.00891	0.00671	0
	(0.0756)	(0.0939)	(0.0816)	
Alone	0.669	0.664	0.668	0
	(0.470)	(0.473)	(0.471)	
Observations	7,782,493	3,317,813	11,100,306	

The columns Females and Males denote the sample averages for females and males respectively in the rows. The third column shows the total average and the last column shows the p-value for a t-test for difference in means between males and females.

Table 2: Reconciling Crime Reports and Arrest Figures

	Crime	Females	Arrested	Females	Defendants	Females	Incarcerated	Females
Larceny	55 %	38 %	61 %	44 %	36 %	31 %	20 %	17 %
Burglary	12 %	15 %	10 %	12 %	37 %	11 %	60 %	5 %
Motor Vehicle	3 %	20 %	3 %	17 %	11 %	16 %	7 %	6 %
Others	27 %	29 %	25 %	28 %	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 committed by females. The fourth column shows from all of the arrested how much were arrested for each crime category, with respectively how much of these arrests were females. The sixth and seventh column show how much of all incarcerated were put behind 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 3: The Earnings Gap in Crime

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Earnings	Earnings	Earnings	Earnings	Earnings	Earnings	Earnings	Earnings
Female	-0.301***	-0.300***	-0.304***	-0.311***	-0.405***	-0.405***	-0.332***	0.142***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)	(0.011)	(0.011)	(0.008)
Age			0.006***	0.006***	0.011***	0.011***	0.008***	0.008***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Weapon				-0.064*	-0.173***	-0.204***	-0.210***	-0.353***
				(0.028)	(0.024)	(0.034)	(0.035)	(0.022)
Female*Weapon				0.103***	0.117***	0.152***	0.094***	-0.191***
				(0.018)	(0.017)	(0.022)	(0.018)	(0.015)
Alone					-0.552***	-0.552***	-0.514***	-0.434***
					(0.014)	(0.014)	(0.013)	(0.007)
Female*Alone					0.118***	0.118***	0.089***	-0.127***
					(0.012)	(0.012)	(0.013)	(0.006)
Gang						0.078	-0.060	0.052
						(0.057)	(0.053)	(0.040)
Female*Weapon						-0.089**	-0.021	-0.087**
						(0.033)	(0.031)	(0.027)
Constant	5.283***	5.283***	5.111***	5.125***	5.378***	5.377***	5.388***	6.159***
	(0.019)	(0.027)	(0.037)	(0.036)	(0.037)	(0.037)	(0.024)	(0.157)
Observations	8640809	8640809	8640809	8640809	8640809	8640809	8640809	8640808
Race controls	-	+	+	+	+	+	+	+
Year*Agency FE	-	-	-	-	-	-	+	+
Offense controls	-	-	-	-	-	-	-	+
Average Gap	-0.301***	-0.300***	-0.304***	-0.308***	-0.323***	-0.323***	-0.271***	0.052***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.007)	(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 4: The Arrest Gap in Crime

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Arrest	Arrest	Arrest	Arrest	Arrest	Arrest	Arrest	Arrest
Female	0.057***	0.053***	0.055***	0.048***	0.072***	0.072***	0.048***	-0.014***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.005)	(0.005)	(0.005)	(0.004)
Age			-0.003***	-0.003***	-0.003***	-0.003***	-0.002***	-0.001***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Weapon				-0.082***	-0.087***	-0.078***	-0.067***	-0.030***
				(0.013)	(0.013)	(0.016)	(0.015)	(0.009)
Female*Weapon				0.039***	0.030***	0.032***	0.034***	0.060***
				(0.006)	(0.006)	(0.007)	(0.008)	(0.006)
Alone					-0.034***	-0.034***	-0.035***	-0.030***
					(0.005)	(0.005)	(0.005)	(0.004)
Female*Alone					-0.035***	-0.035***	-0.029***	0.021***
					(0.004)	(0.004)	(0.003)	(0.002)
Gang						-0.022	-0.015	-0.015
						(0.025)	(0.016)	(0.017)
Female*Gang						-0.007	-0.001	0.007
						(0.011)	(0.009)	(0.009)
Constant	0.326***	0.292***	0.371***	0.389***	0.402***	0.403***	0.417***	0.479***
	(0.007)	(0.010)	(0.014)	(0.012)	(0.013)	(0.013)	(0.007)	(0.019)
Observations	11100306	11100306	11100306	11100306	11100306	11100306	11100306	11100304
Race controls	-	+	+	+	+	+	+	+
Year*Agency FE	-	-	-	-	-	-	+	+
Offense controls	-	-	-	-	-	-	-	+
Average Gap	0.057***	0.053***	0.055***	0.050***	0.050***	0.050***	0.031***	0.002
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(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 5: First stage and Reduced Form

	(1) Men	(2) Women	(3) Men	(4) Women	(5) Men	(6) Women
			Panel A: First stage			
			Log Earnings			
Log lag Earnings	0.352***	0.278***	0.186***	0.137***	0.175***	0.131***
	(0.0221)	(0.0186)	(0.00722)	(0.00613)	(0.00604)	(0.00545)
Log lag Prob. of arrest	-0.0292**	-0.0442***	-0.0511***	-0.0472***	-0.0519***	-0.0462***
	(0.0126)	(0.0149)	(0.00828)	(0.00878)	(0.00868)	(0.00918)
			Log Prob. of arrest			
Log lag Prob. of arrest	0.518***	0.482***	0.387***	0.344***	0.391***	0.349***
	(0.00883)	(0.00976)	(0.00926)	(0.00889)	(0.00969)	(0.00914)
Log lag Earnings	0.000464	0.00149	-0.00467***	-0.000435	-0.00500***	-0.000483
	(0.00232)	(0.00198)	(0.00171)	(0.00135)	(0.00177)	(0.00140)
First stage F-stat	125.1	110.7	336.8	253.4	429.7	290.7
			Panel B: Reduced form			
			Log Crime rates			
Log lag Earnings	0.0404***	0.0159***	0.0572***	0.0381***	0.0534***	0.0358***
	(0.00617)	(0.00531)	(0.00263)	(0.00237)	(0.00264)	(0.00230)
Log lag Prob. of arrest	-0.0646***	-0.0390**	-0.0640***	-0.0688***	-0.0594***	-0.0631***
	(0.0155)	(0.0167)	(0.00681)	(0.00698)	(0.00668)	(0.00711)
Test of equality between men and women (p-value):						
Log lag Earnings	0.000		0.000		0.000	
Log lag Prob. of arrest	0.00857		0.406		0.694	
Typology of Crime FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
County FE	no	no	yes	yes	yes	yes
County FE*Year FE	no	no	no	no	yes	yes
Observations	153,950	138,531	153,950	138,531	153,950	138,531

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Errors are clustered at county level.

Table 6: 2SLS

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Crime rates					
	Men	Women	Men	Women	Men	Women
Log Earnings	0.115***	0.0576***	0.305***	0.278***	0.302***	0.274***
	(0.0178)	(0.0187)	(0.0164)	(0.0197)	(0.0151)	(0.0193)
Log Prob. of arrest	-0.118***	-0.0756**	-0.125***	-0.162***	-0.112***	-0.144***
	(0.0299)	(0.0349)	(0.0165)	(0.0195)	(0.0159)	(0.0197)
Black	1.434***	0.912***	1.282***	1.060***	1.212***	1.022***
	(0.0693)	(0.0419)	(0.0466)	(0.0363)	(0.0501)	(0.0353)
Age 15 - 24	0.206	-0.172	0.986***	1.080***	0.984***	1.143***
	(0.139)	(0.157)	(0.0559)	(0.0731)	(0.0695)	(0.0773)
Age 25 - 34	0.174***	0.319***	0.450***	0.471***	0.467***	0.488***
	(0.0384)	(0.0230)	(0.0179)	(0.0141)	(0.0178)	(0.0146)
Log Wage and salary income	-1.102***	-0.845***	0.128*	0.723***	0.177***	0.819***
	(0.156)	(0.175)	(0.0680)	(0.102)	(0.0633)	(0.102)
Employment rate	3.677***	1.318***	-0.393	-2.078***	-0.705**	-2.401***
	(0.579)	(0.498)	(0.335)	(0.395)	(0.331)	(0.386)
Typology of Crime FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
County FE	no	no	yes	yes	yes	yes
County FE*Year FE	no	no	no	no	yes	yes
Test of equality between men and women (p-value):						
Log Earnings	0.000		0.116		0.0952	
Log Prob. of arrest	0.0230		0.0325		0.0659	
Observations	153,950	138,531	153,950	138,531	153,950	138,531
R-squared	0.488	0.473	0.630	0.629	0.682	0.678

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Errors are clustered at county level.

Table 7: OLS

	(1) Men	(2) Women	(3) Men	(4) Women	(5) Men	(6) Women
	Log Crime rates					
Log Illegal Earnings	0.0649***	0.0465***	0.0877***	0.0757***	0.0836***	0.0724***
	(0.00608)	(0.00531)	(0.00284)	(0.00243)	(0.00271)	(0.00237)
Log Prob. of arrest	-0.0498***	-0.00406	-0.0475***	-0.0268***	-0.0356***	-0.0150**
	(0.0157)	(0.0167)	(0.00754)	(0.00753)	(0.00706)	(0.00729)
Test of equality between men and women (p-value):						
Log Earnings	0.000		0.000		0.000	
Log Prob. of arrest	0.000		0.000		0.000	
Typology of Crime FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
County FE	no	no	yes	yes	yes	yes
County FE*Year FE	no	no	no	no	yes	yes
Observations	153,950	138,531	153,950	138,531	153,950	138,531

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Errors are clustered at county level.

Table 8: Robustness: other specifications

	(1) Men	(2) Women	(3) Men	(4) Women	(5) Men	(6) Women
	Log Crime rates					
WITH MISSING DATA						
Log Illegal Earnings	0.108***	0.0506**	0.245***	0.214***	0.238***	0.211***
	(0.0193)	(0.0209)	(0.0168)	(0.0202)	(0.0163)	(0.0197)
Log Prob. of arrest	-0.154***	-0.100***	-0.184***	-0.222***	-0.158***	-0.190***
	(0.0265)	(0.0327)	(0.0144)	(0.0164)	(0.0142)	(0.0170)
WEIGHTED BY POPULATION						
Log Illegal Earnings	0.142***	0.190***	0.306***	0.351***	0.290***	0.304***
	(0.0441)	(0.0368)	(0.0354)	(0.0387)	(0.0294)	(0.0312)
Log Prob. of arrest	-0.261***	-0.265***	-0.174***	-0.179***	-0.164***	-0.161***
	(0.0607)	(0.0791)	(0.0312)	(0.0338)	(0.0290)	(0.0321)
CONTROLLING FOR WEAPON AND ALONE						
Log Illegal	0.112***	0.0562***	0.296***	0.274***	0.293***	0.270***
	(0.0176)	(0.0187)	(0.0159)	(0.0195)	(0.0148)	(0.0192)
Log Prob. of arrest	-0.119***	-0.0748**	-0.136***	-0.166***	-0.124***	-0.149***
	(0.0298)	(0.0349)	(0.0165)	(0.0195)	(0.0159)	(0.0198)
	Log Number of Crimes					
WITH NUMBER OF CRIMES AS DEP. VARIABLE						
Log Illegal Earnings	0.274***	0.277***	0.337***	0.337***	0.339***	0.340***
	(0.0236)	(0.0231)	(0.0171)	(0.0204)	(0.0152)	(0.0198)
Log Prob. of arrest	-0.210***	-0.217***	-0.120***	-0.136***	-0.109***	-0.123***
	(0.0243)	(0.0257)	(0.0161)	(0.0190)	(0.0157)	(0.0193)

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Errors are clustered at county level.

A Appendix Tables

Table A.1: The Earnings Gap for Different Crimes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
UCR Code	231	232	233	234	235	236	237	238	240	220	120	280	261	262	263	264	265	250	270	210	510
Female	0.077	0.053	0.294***	-0.078***	-0.000	-0.095***	-0.386***	-0.113***	0.055***	-0.063***	-0.004	-0.170**	0.020	0.015	0.003	-0.052	-0.063	-0.094*	-0.235***	-0.011	0.091
	(0.076)	(0.041)	(0.010)	(0.013)	(0.072)	(0.017)	(0.045)	(0.010)	(0.013)	(0.010)	(0.020)	(0.052)	(0.019)	(0.025)	(0.076)	(0.094)	(0.184)	(0.047)	(0.024)	(0.283)	(0.533)
Age	0.001	-0.001	0.011***	0.009***	0.003	0.005***	-0.016***	0.008***	-0.002***	0.001	0.006***	-0.000	0.022***	0.020***	0.018***	-0.002	0.014*	0.013***	0.027***	0.031*	0.035
	(0.002)	(0.002)	(0.001)	(0.000)	(0.005)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.006)	(0.006)	(0.001)	(0.001)	(0.014)	(0.043)
Weapon	-0.132	-0.033	0.073**	-0.628***	-1.500**	-0.412***	-0.280*	-0.383***	-0.059	-0.844***	0.000	-0.032	-1.231***	-0.234	0.138	-0.753***	0.322	-0.688**	0.161	0.000	-0.669
	(0.137)	(0.122)	(0.023)	(0.039)	(0.485)	(0.056)	(0.124)	(0.033)	(0.036)	(0.042)	(.)	(0.184)	(0.114)	(0.226)	(0.242)	(0.150)	(0.526)	(0.248)	(0.321)	(.)	(1.084)
Female*Weapon	-0.240	-0.487	0.071	0.011	0.000	0.123	-0.505	0.067	-0.119	-0.177	0.000	-0.459	0.028	-0.256	-0.271	0.000	0.000	0.119	-0.727	0.000	0.000
	(0.426)	(0.302)	(0.037)	(0.074)	(.)	(0.147)	(0.331)	(0.043)	(0.100)	(0.102)	(.)	(0.476)	(0.211)	(0.520)	(0.327)	(.)	(.)	(0.502)	(0.611)	(.)	(.)
Alone	-0.110	-0.140***	-0.733***	-0.365***	-0.214*	-0.215***	-0.505***	-0.475***	-0.039***	-0.351***	-0.265***	-0.247***	0.133***	-0.184***	-0.321***	-0.147	-0.097	-0.206***	-0.245***	-0.288	-1.325
	(0.067)	(0.043)	(0.015)	(0.011)	(0.098)	(0.014)	(0.035)	(0.012)	(0.009)	(0.008)	(0.014)	(0.054)	(0.039)	(0.034)	(0.073)	(0.552)	(0.255)	(0.039)	(0.030)	(0.511)	(1.508)
Female*Alone	0.036	-0.112	-0.057***	-0.024	0.124	-0.122***	-0.297***	0.070***	0.027*	-0.082***	-0.224***	-0.122	-0.157***	-0.010	0.185*	0.149	0.070	0.091	0.098**	0.020	-4.468
	(0.088)	(0.063)	(0.011)	(0.014)	(0.152)	(0.021)	(0.052)	(0.011)	(0.013)	(0.014)	(0.021)	(0.074)	(0.024)	(0.030)	(0.092)	(0.158)	(0.204)	(0.053)	(0.030)	(0.451)	(2.300)
Gang	0.042	-0.250	0.026	-0.116	0.938	-0.238**	-0.261	-0.046	-0.022	-0.219***	0.229***	-0.340	-0.055	-0.044	-0.036	0.000	0.000	0.371	-0.858	0.094	0.000
	(0.194)	(0.179)	(0.043)	(0.068)	(0.570)	(0.082)	(0.163)	(0.034)	(0.051)	(0.059)	(0.062)	(0.273)	(0.155)	(0.276)	(0.207)	(.)	(.)	(0.530)	(0.483)	(0.596)	(.)
Female*Weapon	-0.009	0.811*	0.002	-0.163	0.000	0.106	0.211	-0.003	0.112	0.095	-0.064**	-0.088	-0.038	-0.605	0.564	0.000	0.000	0.345	0.910	-2.765	0.000
	(0.571)	(0.408)	(0.072)	(0.116)	(.)	(0.202)	(0.379)	(0.057)	(0.166)	(0.138)	(0.024)	(0.730)	(0.303)	(0.768)	(0.532)	(.)	(.)	(0.755)	(0.886)	(4.030)	(.)
Constant	4.712***	4.834***	4.053***	5.383***	4.174***	5.242***	5.952***	5.066***	8.269***	6.367***	5.122***	6.301***	5.040***	5.005***	4.736***	6.108***	5.965***	5.209***	5.752***	5.305***	5.590
	(0.068)	(0.049)	(0.022)	(0.019)	(0.152)	(0.022)	(0.058)	(0.016)	(0.016)	(0.019)	(0.036)	(0.067)	(0.043)	(0.036)	(0.109)	(0.446)	(0.334)	(0.054)	(0.033)	(0.549)	(3.040)
Observations	18177	27256	2333727	717199	13280	410773	102268	1921738	492476	916096	542373	29911	394799	123996	39769	2545	4383	66118	176370	2091	189

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 A.2: The Arrest Gap for Different Crimes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
UCR Code	231	232	233	234	235	236	237	238	240	220	120	280	261	262	263	264	265	250	270	210	510
Female	-0.011	0.013	0.130***	-0.034***	-0.034	-0.093***	-0.089***	-0.046***	-0.056***	-0.073***	0.051***	-0.015*	0.005	-0.008	-0.038***	-0.035	-0.000	-0.007*	0.015**	-0.042	0.031
	(0.015)	(0.013)	(0.009)	(0.003)	(0.025)	(0.005)	(0.010)	(0.004)	(0.005)	(0.003)	(0.007)	(0.006)	(0.003)	(0.005)	(0.009)	(0.027)	(0.024)	(0.003)	(0.005)	(0.025)	(0.040)
Age	-0.001	0.002***	0.000	-0.002***	0.002	-0.002***	-0.002***	-0.001***	-0.005***	-0.001**	0.002***	-0.001***	-0.001***	-0.002***	-0.002***	-0.000	-0.002**	-0.001***	-0.002***	-0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)
Weapon	-0.050	0.029	-0.189***	0.020	0.051	0.027	0.028	-0.014	-0.033**	0.004	0.000	0.039***	0.097***	0.175***	0.097***	0.165	0.154	0.095***	0.015	0.000	0.046
	(0.026)	(0.046)	(0.015)	(0.012)	(0.162)	(0.020)	(0.028)	(0.008)	(0.012)	(0.013)	(.)	(0.008)	(0.012)	(0.034)	(0.012)	(0.094)	(0.261)	(0.012)	(0.032)	(.)	(0.187)
Female*Weapon	0.075	-0.016	-0.049***	-0.023	1.072***	0.005	-0.037	0.003	0.021	0.102***	0.000	-0.004	0.021	-0.021	0.020	-0.157	0.000	0.061	-0.041	0.000	-0.692
	(0.067)	(0.080)	(0.013)	(0.017)	(0.156)	(0.027)	(0.068)	(0.009)	(0.025)	(0.013)	(.)	(0.028)	(0.022)	(0.084)	(0.034)	(0.108)	(.)	(0.034)	(0.089)	(.)	(0.484)
Alone	0.008	-0.034*	0.113***	0.008	-0.032	-0.080***	-0.142***	-0.054***	-0.084***	-0.083***	0.002	-0.134***	-0.013***	-0.041***	-0.078***	0.004	-0.027	-0.028***	-0.004	-0.053*	0.104
	(0.012)	(0.016)	(0.008)	(0.004)	(0.024)	(0.005)	(0.012)	(0.004)	(0.010)	(0.005)	(0.005)	(0.009)	(0.004)	(0.005)	(0.012)	(0.046)	(0.033)	(0.003)	(0.006)	(0.023)	(0.086)
Female*Alone	0.003	0.007	-0.049***	0.014***	-0.077*	-0.012*	0.021	0.026***	-0.005	-0.031***	0.019*	0.012	-0.010**	0.006	0.006	0.038	0.003	-0.001	-0.013*	0.017	-0.018
	(0.017)	(0.017)	(0.005)	(0.003)	(0.038)	(0.006)	(0.012)	(0.003)	(0.006)	(0.003)	(0.008)	(0.007)	(0.003)	(0.006)	(0.009)	(0.029)	(0.026)	(0.003)	(0.006)	(0.029)	(0.055)
Gang	0.090	-0.030	-0.071***	-0.031	-0.144	-0.095***	-0.115***	-0.018	-0.033	-0.048*	0.056***	0.068**	0.030	-0.041	-0.010	0.449***	-0.138	0.067*	0.034	0.092	0.114
	(0.056)	(0.058)	(0.020)	(0.022)	(0.251)	(0.022)	(0.033)	(0.010)	(0.030)	(0.022)	(0.011)	(0.021)	(0.017)	(0.040)	(0.029)	(0.043)	(0.221)	(0.027)	(0.054)	(0.049)	(0.369)
Female*Weapon	-0.030	0.085	0.029	0.026	0.000	0.043	-0.021	0.002	0.019	0.028	0.003	-0.048	-0.002	0.155	0.106	-0.454***	0.130	-0.117	-0.003	-0.208	0.634
	(0.143)	(0.115)	(0.024)	(0.026)	(.)	(0.041)	(0.063)	(0.011)	(0.036)	(0.016)	(0.008)	(0.058)	(0.034)	(0.101)	(0.095)	(0.053)	(0.222)	(0.062)	(0.106)	(0.141)	(0.363)
Constant	0.165***	0.163***	0.508***	0.291***	0.367***	0.398***	0.424***	0.310***	0.497***	0.402***	0.146***	0.453***	0.165***	0.220***	0.316***	0.164***	0.141***	0.167***	0.207***	0.186***	0.209*
	(0.018)	(0.016)	(0.010)	(0.005)	(0.032)	(0.010)	(0.016)	(0.005)	(0.011)	(0.009)	(0.011)	(0.008)	(0.004)	(0.006)	(0.012)	(0.042)	(0.038)	(0.003)	(0.008)	(0.034)	(0.094)
Observations	21315	30664	2500965	811391	18334	485333	116948	2201677	573185	1340229	669339	204399	550907	189813	149461	5475	6550	542412	195696	6668	2034

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.

Table A.3: Unknown Offenders By Crime

UCR	Crime	Mean	SD
231	Pocket-picking	0.11	0.02
232	Purse-snatching	0.08	0.02
233	Shoplifting	0.01	0.00
234	Theft From Building	0.12	0.03
235	Theft From Coin-Operated Machine	0.20	0.06
236	Theft from Motor Vehicle	0.17	0.04
237	Parts	0.21	0.06
238	All Other Larceny	0.13	0.03
240	Motor Vehicle Theft	0.14	0.04
220	Burglary	0.15	0.03
120	Robbery	0.04	0.01
280	Stolen Property Offenses	0.04	0.01
261	Swindle	0.07	0.02
262	Credit Card ATM Fraud	0.11	0.03
263	Impersonation	0.09	0.04
264	Welfare Fraud	0.03	0.02
265	Wire Fraud	0.16	0.04
250	Counterfeiting Forgery	0.07	0.02
270	Embezzlement	0.02	0.01
210	Extortion Blackmail	0.04	0.02
510	Bribery	0.03	0.02
	Average	0.10	

Notes: This table presents the fraction of offenders for whom the gender is not known. The Mean and Standard Deviation are defined over the time series of the sample period 1995 - 2011.

Table A.4: Robustness Checks for the Gender Gap in Crime

	(1)	(2)	(3)	(4)	(5)
	Arrest	Arrest	Arrest	Earnings	Earnings
Female	0.299***	0.186***	-0.004	0.104***	0.249***
	(0.019)	(0.012)	(0.003)	(0.007)	(0.009)
Age	-0.012***	-0.007***	-0.001***	0.008***	0.006***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Weapon	-0.378***	-0.226***	-0.038***	-0.289***	-0.160***
	(0.085)	(0.050)	(0.010)	(0.022)	(0.024)
Female*Weapon	0.181***	0.106***	0.059***	-0.218***	-0.280***
	(0.035)	(0.020)	(0.007)	(0.017)	(0.020)
Alone	-0.157***	-0.095***	-0.013**	-0.492***	-0.568***
	(0.024)	(0.015)	(0.004)	(0.007)	(0.008)
Female*Alone	-0.133***	-0.085***	0.016***	-0.116***	-0.116***
	(0.016)	(0.010)	(0.002)	(0.006)	(0.007)
Gang	-0.125	-0.072	-0.015	0.038	0.078
	(0.139)	(0.080)	(0.020)	(0.038)	(0.044)
Female*Gang	-0.007	-0.007	0.014	-0.100**	-0.087**
	(0.071)	(0.040)	(0.011)	(0.034)	(0.031)
Constant	-0.383***	-0.247***	0.473***	6.248***	5.732***
	(0.055)	(0.034)	(0.027)	(0.198)	(0.213)
Observations	11100306	11100306	7468207	5928009	3175497
Race controls	+	+	+	+	+
Year*Agency FE	-	-	+	+	+
Offense controls	-	-	+	+	+
Estimation:	Logit	Probit			
Subsample:			Daylight	Daylight	Arrested
Average Gap			0.012***	0.007	0.154***
			(0.002)	(0.005)	(0.007)