Conviction, Gender and Labour Market Status: A Propensity Score Matching Approach

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Abstract

This paper applies propensity score matching methods to National Child Development Study dataset to evaluate the effect of conviction on labour market status, paying specific attention to gender differences. Estimation results show that employment is strongly and negatively affected by conviction, while it increases self-employment, unemployment and inactivity. This possibly indicates employers' stigmatization against convicted and discouragement effect after a conviction. However, conviction acts differently between males and females. It reduces employment probabilities by about 10% among males and by about 20% among females. More important, while males recover part of the reduced employment probability moving toward self-employment, conviction results in a strong marginalization on the labour market for females, as unemployment and, overall, inactivity strongly increase. This suggests a stronger discouragement effect for females and a different attitude toward self-employment. Social and economic policies aimed to fight social exclusion and to promote employment of convicted individuals should take into account also the great disadvantage of convicted females.

Keywords: propensity score matching, conviction, gender, labour market status.

JEL codes: J21, J16, K14, C21

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Introduction

In the last two decades the interest of economists on the labour market consequences of conviction has increased, as the number of individuals involved in crime has risen (Holzer, 2007, for a review). Empirical analysis has usually found a negative relationship between criminal records and labour market outcomes (see, for example, Waldfagel, 1994; and Grogger, 1995), even though, more recently, some contradictory results have emerged from studies that stress the role of pre-existing heterogeneity in sorting individuals both into criminal activities and poor labour market performance (see, for example, Freeman, 1992; Nagin and Waldfagel, 1995; Kling, 2006; and Lalonde and Cho, 2008)[1].

Poor labour market outcomes of convicted individuals may be explained in terms of both sides of the labour market. From a supply point of view, since crime is likely to be associated with lower educational attainments and/or skills depreciation, it may result in lower wages and reduced employment opportunities (Myers, 1983). From a demand point of view, both stigma and negative signals, that conviction sends to potential employers, are believed to be the major sources of poor labour market performances of convicted individuals (for example, Freeman, 1999). Stigma, that may be referred to the reluctance of people to interact, economically and socially, with a person who has a criminal record, was investigated both by studies aimed to measure its magnitude (for example Lott 1990, Waldfagel 1994, and Grogger 1995), and those that have tried to explain it from an economic point of view (Rasmusen, 1996; and Sciulli, 2010). At the same time, conviction may be perceived by employers as a negative signal[2] on worker's labour productivity, lower effort and risk of recidivism (Entorf, 2009). In both cases, conviction may result in declining employment probabilities and earnings. Most of the analysis related to crime and labour market outcomes has focused on men, as they represent the greater part of the convicted/incarcerated population. In any case, since the '70s women convicted and/or imprisoned have begun to increase in Britain, and from the '90s conviction and/or imprisonment rates have risen sharply (Home Office, 2002). As Lalonde and Cho (2008) underlined, socioeconomic consequences of incarceration may differ substantially between males and females. Overall, since the typologies of crime that women commit and the loss of related social benefits from committing those crimes, the cost of incarceration may be greater for females than for males (Cho, 2008).

This paper contributes to this literature in various manners. First, as anticipated above, while several studies have investigated the effect of conviction on males, little attention has been devoted to the

[1] Bushway (2004) and Holzer, Raphael and Stoll (2006) apply statistical discrimination thesis to crime and labour market literature to explain the poor labour market performance of ethnic groups (black people) faced with limited access to criminal archives to identify criminals.

[2] Other economists (for example, Nagin and Waldfagel, 1999) argue that conviction may be the only instrument for firms to identify offenders.

effects on females. Here, we compare the effect of conviction on males and females to understand if conviction has different impacts on them: this may be interesting in the light of increasing criminal rates among women. Second, previous studies usually have focused on employment perspective of convicted individuals, while the effects of conviction may affect all labour market status. For example, conviction, because of the stigma effect or negative signals, may be also associated with discouragement favoring inactivity, or preferences for self-employment to avoid to be subjected to employers' stigmatization or negative effects from screening. In any case, allocation among labour market status may be affected by conviction. So, this paper analyzes the causal effect of conviction on all labour market status. Third, the paper applies a propensity score matching approach to determine the causal effect of conviction on labour market status of convicted individuals. This may be relevant as standard econometric methods possibly lead to estimation bias in case of violation of the common support conditions or misspecification of the functional form assumption. This may be particularly true in the case of labour market outcomes of convicted individuals for which confounding factors are likely to determine both conviction and labour market status. Recently, with the purpose of reducing the estimation bias in the estimation of treatment effects with observational data, micro-econometricians (for example Becker and Ichino, 2002; and Black and Smith, 2004) have begun to adopt semi and non parametric techniques (Rosenbaum and Rubin, 1983) to determine the causal effect of a treatment on outcomes of interest. These techniques are based on the "selection on observables" assumptions, for which there exists a set of observed variables such that conditional on these, the impact of treatment is independent of the outcome that would occur without treatment (Conditional Independence Assumption, CIA). However, while applications in various fields of economics have strongly risen in the last years, propensity score matching approach has remained rather unapplied with respect to crime and labour market literature.

The analysis is based on information from various sweeps of the National Child Development Study (NCDS). The 6th sweep, besides to include information on labour market status (our outcomes) employed in 2000 by cohort members, is the only one including questions about conviction (our treatment) records in the time span since the last survey (1991). From the 1st, 3rd and 5th NCDS sweeps we draw information to construct covariates satisfying the balancing properties and correlated both with treatment and outcome, as the propensity score matching method requires in order to be applicable. Our empirical findings suggest that conviction significantly decreases the employment perspective of convicted individuals, while increase inactivity and, slightly, unemployment. Specifically, it seems that conviction results, partly, in a reallocation among labour market status after the conviction and, partly, in a reduction of potential employability chances after conviction. The effects are stronger against females than against males. Specifically, for both males and females the dependent employment rate decreases after conviction possibly as a consequence of employers' stigmatization and negative signals. In any case, the effect against females is doubled with respect to males (about -20% against -10%). Importantly, while the decrease in the dependent employment of males correspond to an increase of both inactivity (+4.3%) and self-employment (+4.2%), the decrease for females correspond to an increase of unemployment (about +5%) and, overall, inactivity (about +14%), suggesting a strong discouragement effect. This indicates conviction is more costly, in terms of labour market opportunities, for females than for males.

The paper is organized as follows. Section 2 describes the data, while section 3 presents the propensity score matching approach. Section 4 discusses the results. Finally, Section 5 concludes.

Data

Econometric analysis is based on the information gathered by 1st, 3rd, 5th and 6th sweeps of the National Child Development Study (NCDS). The NCDS is a continuing longitudinal study that seeks to follow the lives of all those living in England, Scotland and Wales who were born in the first week of March 1958. The main aim of the study is to improve the understanding of the factors affecting human development over the whole lifespan. The NCDS has its origin in the Perinatal Mortality Survey (PMS) that collected information on a cohort of about 17000 children. Subsequently, the PMS became the NCDS that has gathered information on the same individuals at different points in time (1965, 1969, 1974, 1981, 1991, 1999-2000, 2004-2005 and 2008-2009). Specifically, the dataset covers topics such as household, housing, relationships, children, social relationship and support, income, employment, lifelong learning, health, citizenship and values and, finally a self-completion part that includes information about contacts with the police and crime. The 6th NCDS sweep is our reference survey. It took place in 1999-2000, when cohort members were aged 41-42, providing a large set of information over 11000 of the original cohort individuals. The 6th sweep includes information on employment status that allow us to identify four labour market outcomes: employment (EMPL), self-employment (SEMP), unemployment (UNEM) and inactivity (INAC). These information allow us to identify our outcome variables. Overall, the 6th sweep is the only one containing information about conviction experienced during adulthood. Specifically, the question "Been found guilty by a court since the reference date?" is used here to identify individuals with and without conviction records in the time span between 1991 and 1999.

This information is used to identify our treatment variable[3]. Retrospective information from the 1st, 3rd and 5th sweeps are used to construct detailed and wide spectrum pre-treatment covariates. This richness allows us to identify a number of observable variables affecting both treatments and outcomes, for which the CIA is likely to be reliable and the balancing properties are likely to be satisfied. With this in mind, we select the following controls: gender, experience of family problems at age 7 and police trouble at age 16, labour market status at age 33, educational level at age 33, health and disability status at age 33 and regional area at age 33. Table 1 includes descriptive statistics related to the variables used in our analysis.

Table1. Descriptive statistics

		FULL SAMPLE		NON-CONVICTED		CONVICTED	
Type	Variables	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Outcomes	EMPL 2000	0.733	0.443	0.738	0.440	0.622	0.485
	SEMP 2000	0.124	0.330	0.121	0.327	0.193	0.395
	UNEM 2000	0.020	0.141	0.019	0.137	0.042	0.201
	INAC 2000	0.123	0.328	0.122	0.327	0.143	0.351
Treatment	Conviction between 1991-1999	0.042	0.201	-	-	-	-
Controls	Male	0.480	0.500	0.466	0.499	0.812	0.391
	Family problems 1965	0.095	0.293	0.092	0.289	0.158	0.365
	Police trouble 1974	0.138	0.344	0.133	0.339	0.249	0.433
	EMPL 1991	0.691	0.462	0.692	0.462	0.647	0.479
	SEMP 1991	0.112	0.315	0.110	0.312	0.156	0.363
	UNEM 1991	0.034	0.180	0.031	0.174	0.086	0.281
	INAC 1991	0.164	0.371	0.167	0.373	0.111	0.315
	High education1991	0.147	0.354	0.148	0.355	0.109	0.312
	Medium education 1991	0.144	0.351	0.145	0.352	0.126	0.332
	Poor education 1991	0.709	0.454	0.707	0.455	0.765	0.424
	Poor health status 1991	0.015	0.123	0.015	0.122	0.020	0.139
	Disability status 1991	0.153	0.360	0.152	0.359	0.165	0.372
	North-East 1991	0.063	0.243	0.063	0.242	0.074	0.262
	North-West 1991	0.105	0.306	0.106	0.308	0.079	0.270
	Yorkshire-The Humber 1991	0.091	0.287	0.091	0.288	0.086	0.281
	East-Midlands 1991	0.071	0.257	0.071	0.257	0.072	0.258
	South-East 1991	0.306	0.461	0.306	0.461	0.304	0.460
	South-West 1991	0.089	0.285	0.090	0.286	0.079	0.270
	West-Midlands 1991	0.090	0.286	0.090	0.286	0.101	0.302
	East-Anglia 1991	0.039	0.194	0.039	0.194	0.037	0.189
	Wales 1991	0.055	0.228	0.055	0.227	0.059	0.236
	Scotland 1991	0.091	0.287	0.090	0.286	0.109	0.312

Source: own elaboration on NCDS data

Because of some missing information the empirical analysis is based on 9570 individuals, 405 of which have been convicted in the time span between 1991 and 1999 (4.2% of the full sample). The

[3] Individuals declaring to live in prison in 2000 are excluded by our analysis.

sample includes 4611 males (329 of which convicted) and 4959 females (76 of which convicted): conviction rate is higher among males (7.14%) than among females (1.53%), as females only represent 18.8% of convicted individuals. Comparing convicted and non-convicted individuals we note that convicted individuals are more likely associated with family problems at age 7 and police trouble at age 16, as well as lower educational level. Descriptive information also provide preliminary information about the labour market status changes between pre-convicted and post-convicted periods. Looking at that information we note that employment has declined among convicted individuals while it has increased among non-convicted ones. Self-employment has increased more among convicted than among non-convicted suggesting a movement toward jobs less prone to be subjected to stigma. Unemployment has decreased for both sub-groups, while inactivity has clearly declined among non-convicted individuals and has increased among convicted ones. This possibly suggests discouragement effect.

Table 2a provides information on labour market status transitions for the full sample. Looking at the transition matrices we note that persistence in employment is higher among non-convicted than among convicted individuals, while convicted individuals persist more in self-employment and, overall, in unemployment and inactivity. Transitions toward employment, as expected, are higher among non-convicted, while among convicted individuals transitions toward self-employment, unemployment and inactivity are more likely.

Table 2a: Labour market status transition matrix: Full sample

		EMPL-00	SEMP-00	UNEM-00	INAC-00
NON-CONVICTED	EMPL-91	**84.22%**	6.63%	1.49%	7.66%
	SEMP-91	37.23%	**54.85%**	1.29%	6.63%
	UNEM-91	56.60%	12.85%	**12.85%**	17.71%
	INAC-91	57.55%	6.77%	2.08%	**33.59%**
		DEMP-00	SEMP-00	UNEM-00	INAC-00
CONVICTED	EMPL-91	**79.77%**	10.31%	1.53%	8.40%
	SEMP-91	26.98%	**60.32%**	3.17%	9.52%
	UNEM-91	31.43%	22.86%	**22.86%**	22.86%
	INAC-91	33.33%	11.11%	6.67%	**48.89%**

Source: own elaboration on NCDS data

Tables 2b and 2c separate among males and females. They suggest that both groups act quite similarly in terms of direction of effects, even though females seem to be strongly disadvantaged in terms of lower persistence in employment and higher persistence in unemployment and inactivity.

Table 2b: Labour market status transition matrix: Male sample

		EMPL-00	SEMP-00	UNEM-00	INAC-00
NON-CONVICTED	EMPL-91	**86.02%**	8.75%	1.72%	3.50%
	SEMP-91	33.14%	**62.57%**	1.78%	2.51%
	UNEM-91	51.22%	15.12%	**15.12%**	18.54%
	INAC-91	41.84%	4.08%	8.16%	**45.92%**
		DEMP-00	SEMP-00	UNEM-00	INAC-00
CONVICTED	EMPL-91	**83.49%**	10.55%	1.38%	4.59%
	SEMP-91	25.00%	**63.33%**	1.67%	10.00%
	UNEM-91	30.00%	26.67%	**20.00%**	23.33%
	INAC-91	28.57%	14.29%	9.52%	**47.62%**

Source: own elaboration on NCDS data

Table 2c: Labour market status transition matrix: Female sample

		EMPL-00	SEMP-00	UNEM-00	INAC-00
NON-CONVICTED	EMPL-91	**82.27%**	4.34%	1.24%	12.16%
	SEMP-91	45.51%	**39.22%**	0.30%	14.97%
	UNEM-91	69.88%	7.23%	**7.23%**	15.66%
	INAC-91	58.62%	6.95%	1.67%	**32.75%**
		EMPL-00	SEMP-00	UNEM-00	INAC-00
CONVICTED	EMPL-91	**61.36%**	9.09%	2.27%	27.27%
	SEMP-91	66.67%	**0.00%**	33.33%	0.00%
	UNEM-91	40.00%	0.00%	**40.00%**	20.00%
	INAC-91	37.50%	8.33%	4.17%	**50.00%**

Source: own elaboration on NCDS data

The model

We are estimating the causal effect of conviction on labour market status of adult males and females. Ideally, we like to compare the labour market status outcomes of convicted individuals (the treatment group) to the same individuals not experiencing conviction (the control group) to determine the average treatment effect (ATE_j):

$$ATE_j = E\left(Y_j^1 \mid D=1 - Y_j^0 \mid D=0\right) = E\left(Y_j^1 \mid D=1\right) - E\left(Y_j^0 \mid D=0\right) \tag{1}$$

where the subscript j indicates the 2000 labour market status analyzed (EMPL, SEMP, UNEM, INAC), (Y^1_j| D=1) is the outcome of treated Y^1_j if individual was convicted (D=1), and (Y^0_j|D=0), the outcome of untreated (Y^0_j) if individual was not convicted (D=0).

However, as we can observe each individual only in one state, the outcomes for treated had they not been treated is an unobserved counterfactual. To solve this puzzle, micro-econometricians proposed to estimate the average treatment effect on the treated (ATT_j):

$$ATT_j = E\left(Y_j^1 - Y_j^0 \mid D=1\right) = E\left(Y_j^1 \mid D=1\right) - E\left(Y_j^0 \mid D=1\right) \tag{2}$$

That is, the mean effect of being convicted rather than not on the individuals who were convicted (the impact of treatment on the treated). In any case, $Y^0_j|D=1$ is not observable and, as Becker and Ichino (2002) underlined, since in observational studies assignment of subject to the treatment and control groups is not random, the estimation of the effect of treatment may be biased because of the existence of confounding factors[4].

An unbiased estimate of ATT can be obtained if treatment satisfies the Conditional Independence Assumption (CIA):

$$\left(Y^0 \perp D\right) \mid X \tag{3}$$

The outcome of untreated is independent of the treatment conditional on some set of observed covariates X. In other words, according to CIA, conditioning on a suitable set of covariates, it is possible to remove all systematic differences in outcomes in the untreated state. It remains possible that we are not provided with other relevant information that affects both treatments and outcomes (selection on unobservables) but we are confident that the remaining source of selection is substantially reduced as the information provided to us from NCDS is detailed and we are controlling for many channels of indirect correlation.

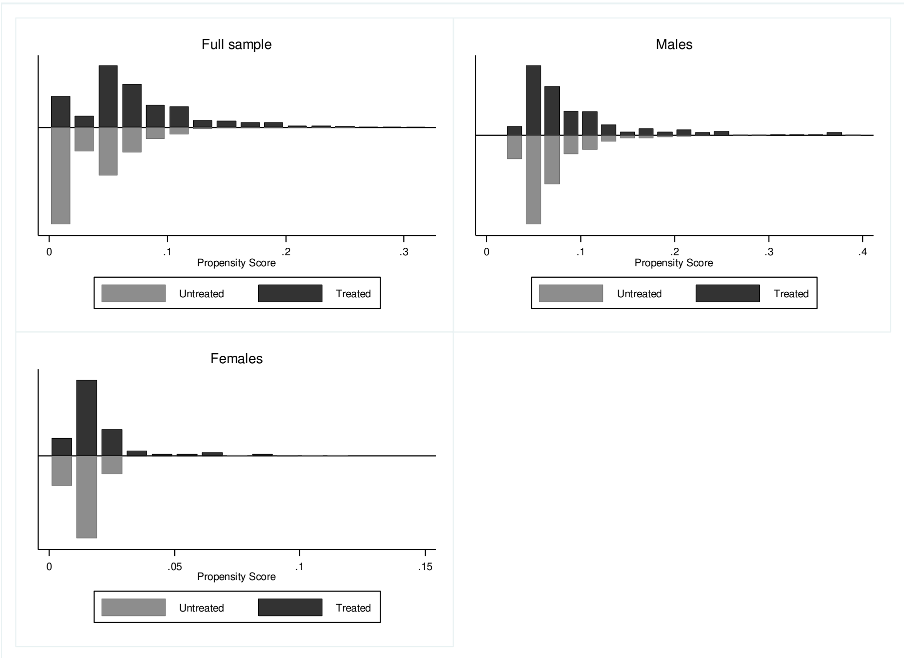
Rosenbaum and Rubin (1983), to reduce the estimation bias in the estimation of treatment effects with observational data, proposed the propensity score matching method. Propensity score matching method has two main advantages when compared with standard econometric techniques. First, it preserves us from making strong assumptions on functional form, like linearity and additivity of regressors, that characterize standard econometric models. Second, propensity score matching is based on the idea that the bias is reduced when the comparison of outcomes is performed using treated and control individuals who are as similar as possible. This is allowed applying the matching procedure based on the propensity score, i.e. the conditional probability of receiving a treatment given pre-treatment characteristics:

$$p(X) \equiv \Pr\left(D=1 \mid X\right) = E\left(D \mid X\right) \tag{4}$$

[4] ATT corresponds to the ATE only if the occurrence of conviction is unrelated to outcomes.

When observations with the same propensity score have the same distribution of observable characteristics independently of treatment status[5], the balancing property is satisfied[6] and, hence, the common support condition holds. Moreover, satisfying the balancing property means that exposure to treatment may be considered to be random and therefore treated and control units should be on average observationally identical (CIA or selection on observables).
To better examine the common support condition the propensity scores of the groups examined are plotted in Figure 1.

Figure 1. Propensity score histograms by treatment status



Source: own elaboration on NCDS data

In the first quadrant, the top histogram reports observations who experienced conviction, while the bottom histogram represents those without conviction. The horizontal axis defines intervals of the propensity score and the height of each bar on the vertical axis indicates the fraction of the relevant sample with scores in the corresponding interval. Similarly, we reported propensity scores for the both gender sub-groups in the second and third quadrants. Fortunately, the figure shows that in all cases the overlapped region is quite wide and it is not needed to eliminate a relevant number of observations.

[5] For a complete discussion on matching methods, see Dehejia and Wahba (2002).
[6] If the balancing property is not satisfied this means that the two groups are too different in terms of observables and additional information would be needed.

Obtaining a specification that satisfies the balancing property does not assure us that we are credibly addressing the possible "selection on unobservables". In other words, it means that bias generated by unobservable confounding factors could be not completely eliminated. The extent to which this bias is reduced depends on the quality and richness of information on which the propensity score is computed. We are confident that information available from the NCDS dataset and that we use quite well satisfy those requirements.

The causal effect we estimate (ATT) corresponds to the total effect: the summation of direct and the indirect effects. In order to identify mediating factors we should use standard parametric methods (as, for example, a Mixed Multinomial Logit) incurring in the problems described above. Anyway, we consider the total effect to be more interesting also from policy perspective.

Matching may be implemented with a variety of different methods. All methods construct an estimate of the expected unobserved counterfactual for each treated observation by taking a weighted average of the outcomes of the untreated observations. What differs is the specific form of the weights. In order to check that our results are not driven by the kind of PSM technique chosen, we use two widely used methods that deal very differently with the trade-off between bias and variance: Gaussian Kernel Matching and Nearest Neighbor Matching. The first is a non-parametric matching estimator that uses weighted averages of all individuals in the control group to generate the counterfactual outcome. One major advantage of these approaches is the smaller variance which is achieved because more information is used. A drawback of these methods is that also observations that are bad matches may be used. Gaussian Kernel matching can be seen as a weighted regression of the counterfactual outcome on an intercept with weights given by the kernel weights. Weights depend on the distance between each individual from the control group and the treated observation for which the counterfactual is estimated (see Smith and Todd, 2005). The second method is the most straightforward matching estimator. An individual from the comparison group is chosen as a matching partner for a treated individual that is closest in terms of propensity score[7].

Estimation results

Propensity score matching results[8] are presented in tables 3, 4 and 5. Table 3 refers to the whole sample, while table 4 and 5 refer, respectively, to the males and females sub-samples estimates. In

[7] For a detailed discussion, see Caliendo and Kopeining (2008).

[8] Difference in Differences (DID) estimator is also used to determine the causal effect of conviction on labour market status. Results point in the same direction of the results from the propensity score matching analysis: dependent employment decreases and inactivity strongly increases overall among women, while men are little affected by

all cases we report the estimated average treatment effects on the treated (ATT) from both matching methods used, i.e. Gaussian Kernel Matching (GKM) and Nearest Neighbor Matching (NMM), and for each labour market status analyzed. Bootstrapped standard errors (500 replications), the resulting t-statistics and the number of treated and untreated (or control) used by each matching technique are also reported in the tables.

We provide some preliminary information, even though GKM and NNM methods differ in the way they deal with the trade-off between bias and efficiency, estimation results are consistent between the matching methods used. On the contrary, magnitude and significance of estimation may differ. This is not surprising as the two considered methods balance very differently between the bias and variance trade-off, with the NNM minimizing bias at the cost of larger variance. This is due to the fact that the number of untreated observations matched with treated is by far larger with the GKM than with the NNM.

Table 3 reports the causal effect of conviction on labour market status for all individuals.

Table 3. The causal effect of conviction on labour market status: full sample

	Gaussian Kernel matching					Nearest Neighbor matching				
EMPL	Treated	Control	ATT	Std. Err.	t	Treated	Control	ATT	Std. Err.	t
	405	9166	**-0.110**	0.023	-4.732	405	5891	**-0.108**	0.025	-4.22
SEMP	Treated	Control	ATT	Std. Err.	t	Treated	Control	ATT	Std. Err.	t
	405	9166	**0.061**	0.02	2.999	405	5891	**0.045**	0.022	2.021
UNEM	Treated	Control	ATT	Std. Err.	t	Treated	Control	ATT	Std. Err.	t
	405	9166	**0.020**	0.01	2.069	405	5891	0.008	0.013	0.576
INAC	Treated	Control	ATT	Std. Err.	t	Treated	Control	ATT	Std. Err.	t
	405	9166	0.029	0.018	1.619	405	5891	**0.055**	0.019	2.834

Source: own elaboration on NCDS data

We find that the estimated ATT for the employment using GKM is - 11.0% while the corresponding NNM estimates show slightly smaller point estimates (- 10.8%). Both estimates are significant at 1% level. The strong negative effect of conviction we find on employment probabilities may be seen as a consequence of employers' stigmatization against convicted individuals and/or the negative signaling that employers draw by observing criminal records. While conviction decreases employment opportunities, it increases the probability of being self-employment. According to GKM the causal total effect corresponds to a + 6.1% (significance at 1% level), while it is + 4.5% according to NNM (significance at 5% level): self-employment substitutes employment. The increase in self-employment rates is possibly indicative that convicted individuals move toward

conviction. Differently, self-employment increases more, but not significantly, among females and unemployment slightly decreases. In any case, the use of propensity score matching is slightly preferred to DID estimator, as DID results may be inconsistent in case outcomes are strongly serially correlated (Bertrand, Duflo and Mullainathan, 2004). DID estimation results are available upon request.

self-employment to recover employment opportunities that they have lost in the labour market because of stigmatization and negative signaling. Perhaps, a part of the effect is explainable in terms of greater inclination to work away from crowded job environments, as a consequence of social stigma, self-isolation or marginalization, because of anti-social behavior possibly associated with criminal activities.

Evidence about the causal effect of conviction on unemployment is less strong. GKM indicates an increase of 2% (significant at 5% level) while according to NNM the effect is smaller (+0.8%) and not significant. The slight increase of unemployment rate may be indicative both of a great substitutability of employment with self-employment and of a relevant discouragement effect, draining labour market participation. This thesis is partly supported by the evidence about the increase of the inactivity rate. However, the positive effect is quite small according to GKM estimator (+2.9% and not significant at 10% level, t-statistics = 1.62), while it is greater and significant according to the NNM estimator (+5.5% and significant at 1% level).

Anyway, the causal effect of conviction quite strongly differ by gender, both in terms of magnitude and labour market status affected. In order to better compare males and females, we comment together tables 4 and 5.

Table 4. The causal effect of conviction on labour market status: male sample

	Gaussian Kernel matching					Nearest Neighbor matching				
EMPL	Treated	Control	ATT	Std. Err.	t	Treated	Control	ATT	Std. Err.	t
	329	4282	**-0.095**	0.024	-3.922	329	3340	**-0.075**	0.029	-2.613
SEMP	Treated	Control	ATT	Std. Err.	t	Treated	Control	ATT	Std. Err.	t
	329	4282	**0.042**	0.022	1.891	329	3340	**0.057**	0.024	2.358
UNEM	Treated	Control	ATT	Std. Err.	t	Treated	Control	ATT	Std. Err.	t
	329	4282	0.009	0.01	0.904	329	3340	-0.001	0.014	-0.053
INAC	Treated	Control	ATT	Std. Err.	t	Treated	Control	ATT	Std. Err.	t
	329	4282	**0.043**	0.016	2.69	329	3340	0.019	0.022	0.849

Source: own elaboration on NCDS data

Table 5. The causal effect of conviction on labour market status: female sample

	Gaussian Kernel matching					Nearest Neighbor matching				
EMPL	Treated	Control	ATT	Std. Err.	t	Treated	Control	ATT	Std. Err.	t
	76	4883	**-0.203**	0.058	-3.509	76	2604	**-0.211**	0.062	-3.414
SEMP	Treated	Control	ATT	Std. Err.	t	Treated	Control	ATT	Std. Err.	t
	76	4883	0.006	0.033	0.179	76	2604	0.018	0.036	0.505
UNEM	Treated	Control	ATT	Std. Err.	t	Treated	Control	ATT	Std. Err.	t
	76	4883	**0.052**	0.027	1.903	76	2604	**0.055**	0.031	1.781
INAC	Treated	Control	ATT	Std. Err.	t	Treated	Control	ATT	Std. Err.	t
	76	4883	**0.145**	0.055	2.616	76	2604	**0.138**	0.057	2.407

Source: own elaboration on NCDS data

Conviction always decreases employment, but the negative effect is clearly stronger against females. In fact, while employment for males decreases by 9.5% according to GKM estimator and by 7.5% according to NNM estimator, both significant at 1% level, conviction reduces employment probabilities of females by 2 times according to GKM estimator (- 20.3%, significant at 1% level) and by three times according to NNM estimator (-21.1%, significant at 1% level). The greater disadvantage for females in terms of employment may be explained in different ways. On the one hand, it is possibly suggestive of a greater stigmatization and negative signalling. On the other hand, stronger discouragement, marginalization and/or scarce attitude to self-employment may be seen as complementary explanations. Looking at table 4, we observe that, for males, after conviction, self-employment increases by 4.2% according to GKM estimator (significant at 10% level) and by 5.7% according to NNM estimator (significant at 5% level), i.e. between about ½ and ¾ of the reduction in employment is compensated by an increase in self-employment. Looking at table 5, we find that conviction does not affect significantly self-employment rates of females and that the magnitude is whatever small. This is possibly indicative of a different behavior of males and females toward self-employment after conviction. While males are strongly attracted by self-employment or are able to do it, self-employment is scarcely attractive or strongly excluding for females. The effect of conviction on unemployment is rather asymmetric with respect to the effects on self-employment. In fact, conviction is completely neutral with respect to male unemployment, while it increases quite strongly unemployment rates of females (+5.2% according to GKM estimator and significant at 10% level, and +5.5% according to NNM estimator and significant at 10% level). This indicates that a share of convicted women, even though not discouraged by conviction are rejected by the labour market, possibly suggesting, one more time, stronger stigmatization and marginalization. The effects on inactivity rates is also interesting. Conviction increases males inactivity according to the GKM estimator (+4.3% significant at 1% level) while the estimation is smaller (+1.9%) and not significant according to NNM. Conviction affects very strongly inactivity rates among females. It increases by 14.5% according to GKM (significant at 1% level) and by 13.8% according to NNM estimator (significant at 1% level). This is possibly indicative of a very strong discouragement effect and/or immobility into non employment positions.

Summarizing, our results point in the direction of a stronger stigmatization and/or marginalization of females after conviction when compared with males. Females not only appear to be strongly discouraged by conviction experiences, but they seem also to have scarce attitude and/or greater difficulties to be integrated into self-employment to recover the loss of employability due to employers' stigmatization and negative signaling, while discouragement seems to prevail. This possibly opens questions for suitable policies aimed to reduce marginalization of women after a conviction and to favor employment opportunities also promoting self-employment to avoid social exclusion.

Conclusions

We apply propensity score matching methods to NCDS dataset to determine the causal effect of conviction during adulthood on labour market status of British adult. Propensity score matching approach, differently from standard econometric techniques, preserves us from the risk of incurring in estimation bias due to misspecification of the functional form assumption and violation of the common support condition.

Empirical evidence points in the direction of a significant and negative effect of conviction on employment probabilities and a slightly positive effect on unemployment. Both results may interpreted as a possible consequence of employers' stigmatization against convicted individuals and negative signalling that employers receive by observing criminal records. Conversely, after a conviction, we find that individuals are more likely to be self-employed or inactive. The increase of self-employment rates may suggest that self-employment possibly becomes an alternative channel to employment for stigmatized individuals, while the increase of inactivity is possibly determined by discouragement due to the adverse labour market conditions after conviction.

Interestingly, we find that conviction acts differently between males and females. Specifically females seem to pay a higher price for conviction than males in terms of reduced labour market opportunities. The reduction of employment is halved for males with respect to females. More importantly, while conviction causes a substantial increase of the self-employment probabilities among males the effect on females is small and not significant. Conversely, conviction determines an increase of unemployment of females and, overall, the increase of inactivity is more than three times greater among females than among males.

Summarizing, while males recover part of the reduced employability moving toward self-employment, conviction results in a strong marginalization on the labour market for females. This is possibly due to both a stronger discouragement of females after conviction and to a different attitude of females toward self-employment or excluding factors (e.g. access to the borrowing) making more hardly their access to this labour market status. Social and economic policies aimed to fight marginalization and to favor employability and social inclusion, should take into account the disadvantage of convicted individuals on the labour market, paying specific attention to the conditions of females. Overall, policies should be aimed to reduce the great disadvantage of convicted women, also promoting specific measures promoting self-employment for females.

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