Conviction, gender and labour market status

Abstract

Applying Propensity Score Matching to the National Child Development Study, we find that conviction reduces the employment probability of middle-aged British females about three times more than comparable males. Moreover, while males recover part of the disadvantage by increasing self-employment, conviction results in a strong labour market marginalization for females, as unemployment and, overall, inactivity increase. Robustness checks tend to confirm these findings. This suggests both a stronger discouragement effect for females and a different attitude toward self-employment or excluding factors (e.g. access to borrowing).

1. 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. Standard results show a negative relationship between crime and labour market outcomes (e.g. Grogger, 1995; Nagin and Waldfagel, 1995). This may be explained both from a supply side perspective, as a consequence of lower educational attainments and/or skills depreciation associated to crime (Myers, 1983), and a demand side perspective, as a consequence of discrimination, stigma or bad signals[1] that conviction sends to potential employers (Freeman, 1999). Nevertheless, studies that stressed the role of unobservable heterogeneity in sorting individuals both into illegal activities and poor labour market performance, found less robust evidence (Kling, 2007; LaLonde and Cho, 2008).

Most of these analyses have focused on men, as they represent the greater part of the convicted/incarcerated population. However, from the '70s, British women involved in illegitimate activities increased, and from the '90s it has risen sharply (National Statistics, 2003). This makes interesting to investigate the labour market outcomes associated to conviction from a gender perspective. With this in mind, first, we compare the effect of conviction on males and females. Second, we focus on the perspectives of convicted individuals in all labour market status[2], rather than just in employment. Third, we adopt a Propensity Score Matching (PSM) approach (Rubin and Rosenbaum, 1983) to estimate the causal effect addressing the selection bias issue.

The analysis is based on information from various sweeps of the National Child Development Study (NCDS). The 6th sweep includes information on 2000 labour market status and conviction records of cohort members in the time span 1991-1999, while from the 1st, 3rd and 5th NCDS sweeps we draw pre-treatment covariates.

The paper is organized as follows. Section 2 describes the data; Section 3 presents the empirical strategy and results; finally, Section 4 concludes.

[1] See Holzer, Raphael and Stoll (2006) for an application of the statistical discrimination thesis, Rasmusen (1996) and Sciulli (2010) for an economic explanation of stigma associated to conviction, and Entorf (2009) for negative signals of worker's productivity.

[2] Conviction, because of stigma or negative signals, may be also associated with discouragement favoring inactivity, or preferences for self-employment to avoid stigmatization or negative effects from screening.

2. Data

2.1 The National Child Development Study

Econometric analysis is based on the NCDS. This is a continuing longitudinal study gathering information on the same individuals, at different points in time (1958, 1965, 1969, 1974, 1981, 1991, 1999-2000, 2004-2005 and 2008-2009), living in Great Britain and who were born in the first week of March 1958. The 6th NCDS sweep is our reference survey. It took place in 1999-2000 and provided a large set of information over 11000 cohort-members. Among others, the 6th sweep includes information on labour market status and the question "Been found guilty by a court since the reference date?", that allows us to identify individuals with and without conviction records in the time span between 1991 and 1999[3]. Information from the 1st, 3rd and 5th sweeps is used to construct detailed and wide spectrum pre-treatment covariates. Specifically, we select the following covariates: experiencing family problems at age 7, the BSAG test-score measuring social maladjustment at age 11, police trouble at age 16, and, at age 33, labour market status[4], educational level, disability status, regional area, and, finally, a dummy approximating the propensity to obey the laws. Related descriptive statistics are presented in Table 1. Because of missing information, our sample is composed by 9605 individuals, 402 of which have been convicted in the time span between 1991 and 1999 (4.2% of the full sample). The sample includes 4606 males (326 of which convicted) and 4999 females (76 of which convicted): the conviction rate is higher among males (7.08%) than among females (1.52%), as females represent 18.7% of convicted individuals[5].

<<Table 1 about here>>

2.2 Data limits

Because the nature of the data, our analysis only includes individuals sentenced to a maximum of eight years' imprisonment, condemned to damages or cautioned. Moreover, as we cannot identify the

[3] We exclude cohort-members living in jail in 2000.
[4]Dehejia and Wahba (2002) argued that estimation bias in matching methods may be reduced by using simple PSM and controlling for past outcomes.
[5] Because the analysis is justified only if performed over the common support region (Heckman et al. 1998), our estimations rely on 4551 males and 4976 females.

timing, the types of crime, and their distribution across gender, we actually estimate an average causal effect with respect to those factors. It follows that the estimated causal effect could be affected by the composition effect. Even though we cannot directly handle this issue, information from the National Statistics (2003) reassures us about the robustness of our findings. In fact, looking at the evolution of indictable offenders and found guilty in the period 1992-2002, the trend is very similar between males and females. Moreover, as crimes associated to greater social stigma (e.g. violence against persons and drug offences), are most common among males than among females, the differences in the estimation results at gender level could be considered as conservative.

3. Empirical analysis

3.1 Selection into illegitimate activities

The theory of participation in illegitimate activities (Becker, 1968) suggests that being convicted is not randomly distributed across individuals[6]. An individual chooses between illegal and legal activities on the basis of their respective expected utility. It could be affected by the earnings from legitimate work, the gain from successful crime, the extent of punishment, the probability of being apprehended and the attitudes toward risk, as well as by other personal attitudes and by previous criminal history (Bowles and Florackis, 2012).

3.2 Econometric method

When operating in a non-experimental setting, the estimation of the causal effect relies on the construction of a counterfactual using observational data of untreated cohort-members. In our context, because of the non-random nature of participation in illegitimate activities, this results in a selection bias problem. This may be econometrically addressed by applying matching estimators (Caliendo and Kopeinig, 2008). Given that we dispose of cross-sectional data, we use the PSM for which the estimated causal effect corresponds to the average treatment effect on the treated (ATT):

$$E(Y_1 \mid p(X), D=1) - E(Y_o \mid p(X), D=0)$$

[6] The gap between selection into crime rather than into conviction depends on the probability of offenders being punished.

where Y_1 is the outcome of convicted cohort members (D=1), Y_0 is the outcome of non-convicted cohort members (D=0), while $p(X)$ is the propensity score, i.e. the probability of being convicted in the 1991-1999 period, given a set of pre-treatment variables (X). In fact, according to the Conditional Independence Assumption (CIA), conditioning on an adequate set of pre-treatment covariates is essential to remove all systematic differences in outcomes in the untreated state and, hence, to address the selection bias problem. Finally, to pair treated and untreated units, we adopt two matching methods: the Gaussian Kernel Matching (GKM) and Nearest Neighbor Matching (NNM), that differ in terms of the strategy adopted to select individual to be included in the control group.

3.3 PSM estimates

PSM results are presented in Tables 2 (Males) and 3 (Females)[7]. Findings are consistent between the matching methods used, while magnitude and significance may differ. The causal effect of a conviction differs by gender, both in terms of magnitude[8] and labour market status affected.

<<Table 2 about here>>

<<Table 3 about here>>

Conviction decreases the employment rate of females three times more than males: -20.2%/- 22.2% against -8.3%/-6.1% (respectively for the GKM and NNM methods). From a demand side perspective, this could be explained by greater stigmatization and negative signaling against females. This could be, for example, because of the greater propensity of females in being employed in jobs subjected to greater stigmatization (jobs requiring a more informal employee-employer relationship, e.g. residential care). From a supply side perspective, this could be because of stronger discouragement or marginalization.

Among males, a conviction increases self-employment rate by +3.7%/+5.4%, contributing to compensate the reduction in employment. Conversely, the effect is not significant for females. This is possibly indicative of a different gender attitude toward self-employment after a conviction.

[7] The estimation results of the propensity score equation and the propensity balancing tests are available upon request.
[8] The employment probabilities are expressed in terms of percentage points.

Conviction is neutral with respect to male unemployment, while it increases unemployment among females (+5.2% according to the GKM estimate). This suggests that a share of convicted women, even though not discouraged, is rejected by the labour market. Finally, conviction increases the inactivity rate of males by 4.1% according to the GKM estimator, while the positive impact is much stronger among females, as it ranges between +14.5%/+14.6%. This possibly indicates a strong discouragement effect and/or persistence into non-employment.

3.4 Robustness checks

A shortcoming of the PSM is that it does not allow to consider the role of unobservable factors, that potentially guide selection into illegitimate activities. This leads to the violation of CIA. We adopt two methods to deal with this issue. First, we use the sensitivity analysis proposed by Ichino, et al. (2008), for which a simulated unobservable factor (*U*) is added to the analysis: new estimated ATTs, including *U*, and baseline ATTs, estimated under the CIA, are compared to uncover the extent of the hypothetical deviation once that the unobservable factor is taken into account. The term *U* is assumed to be distributed similarly to some relevant observable covariates and it can be derived as follows:

$$Pr(U = 1|D = i, Y = j, X) = Pr(U = 1|D = i, Y = j) \equiv pij$$

with $i, j \in \{0,1\}$, which correspond to the probability that *U*=1 in each of the four groups defined by the treatment status D_i and the outcome value Y_j.

Second, we run difference-in-differences (DiD) estimations. DiD allow us to determine the causal effect comparing the difference between outcomes at two time points for both treated and control groups. This allows to take into account time-invariant unobserved heterogeneity correlated both with the treatment and the outcome variables.

Results of robustness checks are presented in the Appendix. Sensitivity analysis (Tables A1 and A2) highlights two main points. First, the presence of potential confounders is not negligible; hence PSM estimation is potentially biased. Second, the bias does not change the essence of PSM results. In fact, a) among males, conviction reduces employment and increases self-employment, while unemployment and inactivity are negligibly affected; b) among females, conviction strongly reduces employment and increases unemployment and, overall, inactivity.

Finally, DiD estimates (Table A3) confirm both the negligible effects of a conviction on labour market perspectives of males and the labour market marginalization of females.

Conclusions

We apply PSM to the NCDS to investigate the causal effect of a conviction on labour market status of middle-aged British males and females. We find that females pay off a three times greater price for conviction than males in terms of employment rate. Moreover, while conviction determines an increase of self-employment probability among males, it results in increasing unemployment and, overall, inactivity for females. Robustness checks suggest that the effect for males is negligible, and confirm the negative impact on labour force participation of females. The stronger marginalization of females could be explained both in terms of discouragement of females after conviction and to a different attitude of females toward self-employment or excluding factors (e.g. access to borrowing) making harder their access to this labour market status.

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Table1. Descriptive statistics

	Males					Females				
	Non-convicted		Convicted			Non-convicted		Convicted		
	mean	std. dev.	mean	std. dev.		mean	std. dev.	mean	std. dev.	
Employment	0.750	0.433	0.644	0.479	***	0.727	0.446	0.526	0.503	***
Self-employment	0.174	0.379	0.219	0.414	**	0.075	0.264	0.079	0.271	
Unemployment	0.025	0.157	0.036	0.188		0.014	0.118	0.066	0.250	***
Inactive	0.050	0.219	0.100	0.301	***	0.184	0.388	0.329	0.473	***
Employment in 1991	0.772	0.420	0.663	0.474	***	0.623	0.485	0.579	0.497	
Self-employment in 1991	0.158	0.364	0.182	0.387		0.068	0.252	0.039	0.196	
Unemployment in 1991	0.048	0.213	0.091	0.288	***	0.017	0.129	0.066	0.250	***
Inactive in 1991	0.023	0.149	0.064	0.245	***	0.292	0.455	0.316	0.468	
Disabled	0.167	0.373	0.167	0.374		0.140	0.347	0.158	0.367	
Ethnic	0.021	0.143	0.028	0.164		-	-	-	-	
Missing education	0.022	0.146	0.024	0.154		0.017	0.130	0.026	0.161	
Poor education	0.680	0.466	0.772	0.420	***	0.730	0.444	0.737	0.443	
Medium education	0.151	0.358	0.122	0.327		0.140	0.347	0.145	0.354	
High education	0.169	0.375	0.106	0.309	***	0.130	0.336	0.118	0.325	
North-East	0.061	0.239	0.079	0.270		0.064	0.245	0.053	0.225	
North-West	0.103	0.304	0.073	0.260	*	0.108	0.311	0.105	0.309	
Yorkshire	0.091	0.288	0.088	0.284		0.091	0.287	0.079	0.271	
East-Midlands	0.080	0.272	0.079	0.270		0.063	0.243	0.039	0.196	
South-East	0.306	0.461	0.292	0.455		0.307	0.461	0.355	0.482	
South-West	0.086	0.281	0.088	0.284		0.092	0.290	0.039	0.196	*
West-Midlands	0.094	0.292	0.100	0.301		0.086	0.280	0.105	0.309	
East-Anglia	0.036	0.187	0.036	0.188		0.042	0.200	0.039	0.196	
Wales	0.054	0.226	0.067	0.250		0.055	0.228	0.026	0.161	
Scotland	0.088	0.283	0.097	0.297		0.092	0.289	0.158	0.367	**
Family problem at age 7	0.085	0.279	0.173	0.379	***	0.098	0.297	0.092	0.291	
BSAG score at age 11	7.435	8.764	10.040	10.190	***	5.411	7.155	8.724	11.303	***
Missing BSAG score at age 11	0.134	0.341	0.125	0.331		0.134	0.341	0.145	0.354	
Police trouble at age 16	0.160	0.367	0.274	0.446	***	0.108	0.311	0.145	0.354	
Law obeyed at age 33	0.492	0.500	0.429	0.496	**	0.496	0.500	0.447	0.501	
Missing law obeyed at age 33	0.047	0.212	0.076	0.265	**	0.036	0.186	0.092	0.291	***

Source: our elaboration based on NCDS data. Note: fifth and tenth columns report the significance of the t-test statistics conducted on the mean values of the listed variables.

Table 2. PSM estimation: Males

	Gaussian Kernel Matching					Nearest Neighbor Matching				
Labour market status	treat.	contr.	ATT	Std. Err.	t	treat.	contr.	ATT	Std. Err.	t
EMPL	326	4225	**-0.083**	0.025	-3.287	326	719	**-0.061**	0.036	-1.684
SELFSEMP	326	4225	**0.037**	0.021	1.805	326	719	**0.054**	0.030	1.807
UNEM	326	4225	0.005	0.011	0.433	326	719	-0.002	0.018	-0.125
INAC	326	4225	**0.041**	0.017	2.452	326	719	0.009	0.025	0.366

Note. Our elaboration based on NCDS data. PSM estimations performed by using the STATA commands *attk* and *attnd*. *T-stats* are obtained by using bootstrapped standard errors (500 replications).

Table 3. PSM estimation: Females

	Gaussian Kernel Matching					Nearest Neighbor Matching				
Labour market status	treat.	contr.	ATT	Std. Err.	t	treat.	contr.	ATT	Std. Err.	t
EMPL	76	4900	**-0.202**	0.056	-3.610	76	270	**-0.222**	0.081	-2.731
SEMP	76	4900	0.005	0.031	0.170	76	270	0.031	0.043	0.714
UNEM	76	4900	**0.052**	0.029	1.800	76	270	0.045	0.033	1.352
INAC	76	4900	**0.145**	0.055	2.620	76	270	**0.146**	0.071	2.051

Note. Our elaboration based on NCDS data. PSM estimations performed by using the STATA commands *attk* and *attnd*. *T-stats* are obtained by using bootstrapped standard errors (500 replications).

Appendix

Table A1. Sensitivity analysis: Males

								GKM				NNM			
		p11	p10	p01	p00	p1.	p0.	ATT	Outcome	Selection	Change	ATT	Outcome	Selection	Change
EMPL	Baseline	0.00	0.00	0.00	0.00	0.00	0.00	-0.083	-	-	-	-0.061	-	-	-
	Disability	0.14	0.21	0.16	0.19	0.17	0.17	-0.083	0.816	1.021	0.00%	-0.030	0.817	0.983	-50.82%
	Ethnic	0.04	0.01	0.02	0.02	0.03	0.02	-0.083	0.896	1.351	0.00%	-0.023	0.892	1.284	-62.30%
	High education	0.11	0.09	0.18	0.14	0.11	0.17	-0.081	0.863	2.263	-2.41%	-0.025	1.319	0.597	-59.02%
	Family problems	0.17	0.18	0.08	0.10	0.17	0.09	-0.079	0.863	2.311	-4.82%	-0.032	0.849	2.212	-47.54%
	Police trouble	0.23	0.36	0.16	0.17	0.27	0.16	-0.078	0.903	1.956	-6.02%	-0.034	0.887	1.977	-44.26%
	High BSAG	0.31	0.46	0.23	0.29	0.36	0.24	-0.078	0.739	1.739	-6.02%	-0.030	0.725	1.768	-50.82%
	Law obeyed	0.51	0.37	0.53	0.47	0.46	0.52	-0.082	1.267	0.826	-1.20%	-0.032	1.274	0.834	-47.54%
								GKM				NNM			
		p11	p10	p01	p00	p1.	p0.	ATT	Outcome	Selection	Change	ATT	Outcome	Selection	Change
SEMP	Baseline	0.00	0.00	0.00	0.00	0.00	0.00	0.037	-	-	-	0.054	-	-	-
	Disability	0.19	0.16	0.14	0.17	0.17	0.17	0.037	0.779	1.017	0.00%	0.033	0.784	1.004	-38.89%
	Ethnic	0.01	0.03	0.03	0.02	0.03	0.02	0.037	1.483	1.280	0.00%	0.030	1.430	1.304	-44.44%
	High education	0.11	0.11	0.17	0.17	0.11	0.17	0.037	0.947	0.592	0.00%	0.037	0.978	0.587	-31.48%
	Family problems	0.14	0.18	0.07	0.09	0.17	0.09	0.037	0.879	2.221	0.00%	0.039	0.835	2.371	-27.78%
	Police trouble	0.25	0.28	0.15	0.16	0.27	0.16	0.037	0.950	2.006	0.00%	0.036	0.923	1.975	-33.33%
	High BSAG	0.39	0.35	0.24	0.24	0.36	0.24	0.037	0.988	1.783	0.00%	0.036	0.962	1.763	-33.33%
	Law obeyed	0.40	0.48	0.49	0.52	0.46	0.52	0.037	0.872	0.814	0.00%	0.034	0.898	0.818	-37.04%
								GKM				NNM			
		p11	p10	p01	p00	p1.	p0.	ATT	Outcome	Selection	Change	ATT	Outcome	Selection	Change
UNEM	Baseline	0.00	0.00	0.00	0.00	0.00	0.00	0.005	-	-	-	-0.002	-	-	-
	Disability	0.25	0.16	0.17	0.17	0.17	0.17	0.005	0.994	1.022	0.00%	-0.011	1.028	1.019	450.00%
	Ethnic	0.00	0.03	0.01	0.02	0.03	0.02	0.005	0.717	1.365	0.00%	-0.010	0.693	1.417	400.00%
	High education	0.08	0.11	0.05	0.17	0.11	0.17	0.004	0.255	0.592	-20.00%	-0.013	0.237	0.587	550.00%
	Family problems	0.25	0.17	0.15	0.08	0.17	0.09	0.002	1.893	2.201	-60.00%	-0.014	1.844	2.247	600.00%
	Police trouble	0.67	0.26	0.25	0.16	0.27	0.16	0.001	1.834	1.96	-80.00%	-0.015	1.902	1.988	650.00%
	High BSAG	0.67	0.35	0.40	0.24	0.36	0.24	0.001	2.226	1.756	-80.00%	-0.011	2.190	1.735	450.00%
	Law obeyed	0.38	0.47	0.46	0.52	0.46	0.52	0.004	0.833	0.81	-20.00%	-0.009	0.803	0.811	350.00%
								GKM				NNM			
		p11	p10	p01	p00	p1.	p0.	ATT	Outcome	Selection	Change	ATT	Outcome	Selection	Change
INAC	Baseline	0.00	0.00	0.00	0.00	0.00	0.00	0.041	-	-	-	0.009	-	-	-
	Disability	0.24	0.16	0.37	0.16	0.17	0.17	0.041	3.294	0.978	0.00%	0.009	3.333	0.983	0.00%
	Ethnic	0.00	0.03	0.01	0.02	0.03	0.02	0.041	0.75	1.301	0.00%	0.005	0.820	1.413	-44.44%
	High education	0.06	0.11	0.11	0.17	0.11	0.17	0.040	0.549	0.604	-2.44%	-0.001	0.579	0.590	-111.11%
	Family problems	0.24	0.17	0.14	0.08	0.17	0.09	0.038	1.752	2.263	-7.32%	0.003	1.892	2.268	-66.67%
	Police trouble	0.48	0.25	0.21	0.16	0.27	0.16	0.039	1.409	1.926	-4.88%	0.005	1.437	1.940	-44.44%
	High BSAG	0.55	0.34	0.41	0.23	0.36	0.24	0.038	2.324	1.736	-7.32%	0.003	2.310	1.765	-66.67%
	Law obeyed	0.30	0.48	0.40	0.52	0.46	0.52	0.040	0.617	0.816	-2.44%	0.008	0.629	0.818	-11.11%

Note. Our elaboration based on NCDS data. Estimates obtained by using the STATA 11 routine "*sensatt*". Replications set at 500. High BSAG is a dummy variable taking value one if the BSAG score belongs to the fourth quartile of the BSAG score distribution.

Table A2. Sensitivity analysis: Females

								GKM				NNM			
		p11	p10	p01	p00	p1.	p0.	ATT	Outcome	Selection	Change	ATT	Outcome	Selection	Change
EMPL	Baseline	0.00	0.00	0.00	0.00	0.00	0.00	-0.202	-	-	-	-0.222	-	-	-
	Disability	0.17	0.14	0.12	0.18	0.16	0.14	-0.202	0.641	1.171	0.00%	-0.177	0.642	1.179	-20.27%
	High education	0.15	0.08	0.13	0.14	0.12	0.13	-0.202	0.934	0.903	0.00%	-0.182	0.930	0.953	-18.02%
	Family problems	0.05	0.14	0.09	0.11	0.09	0.10	-0.202	0.824	0.916	0.00%	-0.183	0.864	0.961	-17.57%
	Police trouble	0.03	0.28	0.10	0.12	0.14	0.11	-0.202	0.837	1.434	0.00%	-0.181	0.855	1.400	-18.47%
	High BSAG	0.20	0.50	0.25	0.28	0.34	0.26	-0.202	0.860	1.494	0.00%	-0.182	0.864	1.548	-18.02%
	Law obeyed	0.59	0.38	0.52	0.49	0.49	0.51	-0.202	1.134	0.955	0.00%	-0.178	1.151	0.962	-19.82%
								GKM				NNM			
		p11	p10	p01	p00	p1.	p0.	ATT	Outcome	Selection	Change	ATT	Outcome	Selection	Change
SEMP	Baseline	0.00	0.00	0.00	0.00	0.00	0.00	0.005	-	-	-	0.031	-	-	-
	Disability	0.00	0.17	0.12	0.14	0.16	0.14	0.005	0.826	1.177	0.00%	-0.001	0.818	1.166	-103.23%
	High education	0.00	0.13	0.19	0.13	0.12	0.13	0.006	1.616	0.921	20.00%	0.001	1.607	0.916	-96.77%
	Family problems	0.00	0.10	0.07	0.10	0.09	0.10	0.005	0.68	0.948	0.00%	-0.002	0.608	0.985	-106.45%
	Police trouble	0.17	0.14	0.11	0.11	0.14	0.11	0.005	1.008	1.431	0.00%	0.000	0.967	1.394	-100.00%
	High BSAG	0.33	0.34	0.21	0.26	0.34	0.26	0.006	0.731	1.524	20.00%	-0.003	0.724	1.490	-109.68%
	Law obeyed	0.40	0.50	0.47	0.52	0.49	0.51	0.005	0.831	0.898	0.00%	0.000	0.853	0.932	-100.00%
								GKM				NNM			
		p11	p10	p01	p00	p1.	p0.	ATT	Outcome	Selection	Change	ATT	Outcome	Selection	Change
UNEM	Baseline	0.00	0.00	0.00	0.00	0.00	0.00	0.052	-	-	-	0.045	-	-	-
	Disability	0.00	0.17	0.22	0.14	0.16	0.14	0.052	1.788	1.23	0.00%	0.044	1.790	1.155	-2.22%
	High education	0.00	0.13	0.12	0.13	0.12	0.13	0.052	0.889	0.9	0.00%	0.041	0.908	0.862	-8.89%
	Family problems	0.20	0.08	0.16	0.10	0.09	0.10	0.052	1.794	0.988	0.00%	0.040	1.738	0.902	-11.11%
	Police trouble	0.20	0.14	0.10	0.11	0.14	0.11	0.052	0.936	1.38	0.00%	0.043	1.008	1.429	-4.44%
	High BSAG	0.40	0.34	0.28	0.26	0.34	0.26	0.052	1.108	1.48	0.00%	0.045	1.109	1.527	0.00%
	Law obeyed	0.50	0.49	0.45	0.52	0.49	0.51	0.052	0.761	0.93	0.00%	0.043	0.764	0.974	-4.44%
								GKM				NNM			
		p11	p10	p01	p00	p1.	p0.	ATT	Outcome	Selection	Change	ATT	Outcome	Selection	Change
INAC	Baseline	0.00	0.00	0.00	0.00	0.00	0.00	0.145	-	-	-	0.146	-	-	-
	Disability	0.20	0.14	0.20	0.13	0.16	0.14	0.145	1.803	1.190	0.00%	0.138	1.774	1.145	-5.48%
	High education	0.12	0.12	0.12	0.13	0.12	0.13	0.145	0.872	0.858	0.00%	0.139	0.854	0.942	-4.79%
	Family problems	0.16	0.06	0.12	0.09	0.09	0.10	0.145	1.388	0.900	0.00%	0.141	1.390	0.972	-3.42%
	Police trouble	0.32	0.06	0.13	0.10	0.14	0.11	0.145	1.308	1.453	0.00%	0.137	1.305	1.333	-6.16%
	High BSAG	0.56	0.24	0.31	0.25	0.34	0.26	0.145	1.403	1.490	0.00%	0.133	1.411	1.468	-8.90%
	Law obeyed	0.35	0.57	0.50	0.52	0.49	0.51	0.145	0.958	0.951	0.00%	0.136	0.941	0.931	-6.85%

Note. Our elaboration based on NCDS data. Estimates obtained by using the STATA 11 routine "*sensatt*". Replications set at 500. High BSAG is a dummy variable taking value one if the BSAG score belongs to the fourth quartile of the BSAG score distribution.

Table A3. DiD estimations

		Males			Females		
		Difference		DiD	Difference		DiD
		Pre-treatment	Post-treatment		Pre-treatment	Post-treatment	
EMPL	Estimate	-0.089	-0.102	-0.013	-0.028	-0.184	**-0.156**
	Std. Err.	0.027	0.026	0.038	0.054	0.058	0.079
		***	***			***	**
SEMP	Estimate	0.025	0.044	0.019	-0.025	0.007	0.032
	Std. Err.	0.024	0.025	0.046	0.025	0.032	0.039
UNEM	Estimate	0.012	-0.006	**-0.018**	0.047	0.050	0.003
	Std. Err.	0.006	0.002	0.010	0.028	0.029	0.039
		**	***	*	*	*	
INAC	Estimate	0.028	0.040	0.012	0.006	0.127	**0.121**
	Std. Err.	0.012	0.017	0.029	0.048	0.054	0.073
		**	**			**	*

Note. Our elaboration based on NCDS data.