A Online Appendix: Tables and Figures.

The effects of DNA databases on the deterrence and detection of offenders

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Table A-1: Crime categories

Criminal Code	Main categories of crime	Subcategories of crime	Our category
Penal Code	All sexual offenses	Incest	Sexual
		Rape	Sexual
		Pedophilia	Sexual
		Voyerism, flashing	Sexual
		Other sexual violations	Sexual
	Violent crime	Violence against public servant	Violence
		Disturbance of public peace	Violence
		Murder, manslaughter (+ attempted)	Violence
		Simple violence	Violence
		Major violence	Violence
		Threats	Violence
		Other violent assaults	Violence
	Property crimes	Fraud	Property
		Arson	Property
		Theft	Property
		Burglary	Property
		Robbery	Property
		Vandalism	Property
		Other property crime	Property
	Other crimes against penal code	Crimes against/as a public servant	Other (penal)
		Drug smuggling or sales	Other (penal)
		Obstruction of justice	Other (penal)
		Restrain orders	Other (penal)
		Other crimes, penal code	Other (penal)
Special Acts	Violations of Traffic Act	Accidents and speeding	-
		Traffic accidents w. alcohol	-
		Drunk driving	-
		Other traffic offenses	-
	Violations of Drug Act	Possession and or drugs sales -	
	Violations of Weapons/Arms Act	Explosives, firearms, knives	Weapon
	Smuggling, construction, health, social fraud, other		-

Table A-2: Effects of DNA profiling on subsequent convictions (accumulated) by different caps on prior charges

	P(convicted)			**# convictions**		
	Max. 5	Max. 10	Max. 15	Max. 5	Max. 10	Max. 15
1 year	-0.053**	-0.065***	-0.078***	-0.055*	-0.093**	-0.116***
	(0.019)	(0.019)	(0.020)	(0.026)	(0.029)	(0.031)
2 years	-0.058*	-0.075**	-0.080***	-0.098*	-0.163***	-0.190***
	(0.025)	(0.024)	(0.023)	(0.044)	(0.048)	(0.050)
3 years	-0.024	-0.047+	-0.053*	-0.061	-0.129*	-0.153*
	(0.027)	(0.025)	(0.024)	(0.057)	(0.061)	(0.064)
Observations	51550	66911	76531	51550	66911	76531

Standard errors in parentheses + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$ Note: Table shows 2SLS estimates of regressing subsequent crime on DNA registration (instrumented by timing of initial charge - before/after reform) by different caps on prior charges. Covariates include age, immigrant background, has children, single, years of education, gross income, employment status, number of prior charges, crime type dummies and month fixed effects. Standard errors are clustered by personal identification number. Source: Own calculations based on Data from Statistics Denmark and the National Police.

Table A-3: Mean of crime and family outcomes, by timing of charge relative to the reform

	Pre reform	Post reform	Pre reform	Post reform	Pre reform	Post reform
A) Crime outcomes:	*P(conviction)*		*# convictions*			
Any Crime						
1 year	0.153	0.114	0.189	0.133		
2 years	0.298	0.246	0.449	0.341		
3 years	0.375	0.338	0.652	0.553		
Property						
1 year	0.091	0.058	0.111	0.067		
2 years	0.186	0.136	0.263	0.176		
3 years	0.238	0.198	0.375	0.292		
Violence						
1 year	0.049	0.044	0.053	0.047		
2 years	0.103	0.096	0.120	0.112		
3 years	0.141	0.138	0.177	0.170		
Sexual						
1 year	0.002	0.001	0.002	0.001		
2 years	0.003	0.002	0.003	0.002		
3 years	0.005	0.003	0.005	0.004		
Other penal						
1 year	0.012	0.008	0.012	0.009		
2 years	0.034	0.026	0.036	0.027		
3 years	0.051	0.047	0.055	0.050		
Weapon						
1 year	0.011	0.009	0.011	0.009		
2 years	0.026	0.023	0.027	0.024		
3 years	0.038	0.035	0.041	0.037		
Observations	34829	32082	34829	32082		
B) Labor Market outcomes:	*Employment*		*Education/training*		*Unemployment*	
Cumulated time year 1-4	1.954	1.878	0.120	0.212	1.926	1.910
Observations	34829	32082	34829	32082	34829	32082
C) Family outcomes:	*Married*		*Same partner*		*Living with child and mother*	
1 year	0.058	0.042	0.467	0.444	0.307	0.290
2 years	0.064	0.050	0.418	0.390	0.288	0.268
3 years	0.075	0.064	0.386	0.347	0.280	0.252
Observations	34829	32082	5106	4421	6614	5153

Note: The table shows means of crime, labor market and family outcomes for those charged before and after the reform separately. Source: Own calculations based on Data from Statistics Denmark.

Table A-4: Charges and convictions for crimes committed before DNA profiling

	P(charged)	# charges	P(convicted)	# convictions
3 years	-0.006	0.033	-0.009	-0.011
	(0.020)	(0.061)	(0.013)	(0.015)
Observations	66911	66911	66911	66911

Note: The table shows estimated changes in the probability of being charged, number of charges, probability of being convicted, and number of convictions for crimes committed *before* DNA profiling but where charges were not pressed until *after* the DNA profiling. Source: Own calculations based on Data from Statistics Denmark and the National Police.

Table A-5: Effects of DNA registration on subsequent accumulated probability of conviction and number of convictions, by crime type

	By initial crime type		By subsequent crime type	
	P(conviction)	# convictions	P(conviction)	# convictions
A: Property				
1 year	-0.053^{+}	-0.089*	-0.031^{+}	-0.051*
	(0.029)	(0.044)	(0.016)	(0.023)
2 years	-0.073*	-0.170*	-0.049*	-0.087*
	(0.035)	(0.074)	(0.021)	(0.038)
3 years	-0.036	-0.097	-0.037^{+}	-0.062
	(0.036)	(0.095)	(0.022)	(0.049)
B: Violence				
1 year	-0.067**	-0.077**	-0.031*	-0.035*
	(0.021)	(0.028)	(0.012)	(0.014)
2 years	-0.085**	-0.129**	-0.034*	-0.041^{+}
	(0.027)	(0.045)	(0.017)	(0.022)
3 years	-0.066*	-0.129*	-0.026	-0.027
	(0.029)	(0.059)	(0.020)	(0.028)
C: Sexual				
1 year	0.019	0.015	-0.000	-0.000
	(0.040)	(0.045)	(0.002)	(0.002)
2 years	0.063	0.023	0.001	0.001
	(0.064)	(0.089)	(0.003)	(0.003)
3 years	0.071	0.025	0.004	0.002
	(0.073)	(0.061)	(0.004)	(0.004)
D: Other penal				
1 year	-0.119*	-0.173*	0.001	0.004
	(0.060)	(0.081)	(0.006)	(0.006)
2 years	-0.035	-0.219^{+}	-0.013	-0.014
	(0.082)	(0.131)	(0.010)	(0.011)
3 years	-0.095	-0.362*	0.004	-0.008
	(0.087)	(0.163)	(0.013)	(0.014)
E: Weapon				
1 year	-0.319	-0.425	-0.010^{+}	-0.011^{+}
	(0.230)	(0.301)	(0.006)	(0.006)
2 years	-0.398	-0.862^{+}	-0.021*	-0.021*
	(0.286)	(0.502)	(0.009)	(0.009)
3 years	-0.102	-0.593	-0.031**	-0.034**
	(0.290)	(0.616)	(0.011)	(0.012)
Pre-reform baseline, 1 year				
Property	0.168	0.209	0.091	0.111
Violence	0.140	0.165	0.049	0.053
Sexual	0.042	0.043	0.002	0.002
Other penal	0.113	0.143	0.012	0.012
Weapon	0.159	0.193	0.011	0.011

Standard errors in parentheses. $^{+}$ $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Note: Table shows estimates of the effect of DNA registration by type of initial crime in the left half and the type of subsequent crime in the right half. Total number of observations: 66,991. Observations by initial crime type: property 37,443; violence 18,116; sexual 1,576; other penal 5,735; weapon 4,041. Covariates include age, immigrant background, has children, single, years of education, gross income, employment status, number of prior charges, crime type dummies and month fixed effects. Standard errors are clustered by personal identification number. Source: Own calculations based on Data from Statistics Denmark and the National Police.

Table A-6: Effects of DNA profiling, heterogeneity by offender characteristics

	Panel A		**Panel B**		**Panel C**	
	First sample	Recidivist charge	Aged 18-23	Aged 24-30	Child	No child
P(convicted)						
1 year	-0.048^{+}	-0.068**	-0.090***	0.002	-0.048	-0.067**
	(0.025)	(0.023)	(0.023)	(0.033)	(0.050)	(0.021)
2 years	-0.081*	-0.071*	-0.085**	-0.050	-0.141*	-0.067**
	(0.035)	(0.028)	(0.028)	(0.043)	(0.066)	(0.025)
3 years	-0.030	-0.049^{+}	-0.050^{+}	-0.044	-0.115^{+}	-0.039
	(0.040)	(0.029)	(0.029)	(0.046)	(0.069)	(0.026)
Pre-reform baseline (1 year)	0.061	0.183	0.177	0.107	0.124	0.157
# convictions						
1 year	-0.037	-0.105**	-0.130***	0.004	-0.063	-0.097**
	(0.028)	(0.035)	(0.035)	(0.048)	(0.072)	(0.031)
2 years	-0.065	-0.182**	-0.189**	-0.093	-0.193^{+}	-0.159**
	(0.048)	(0.058)	(0.058)	(0.080)	(0.116)	(0.051)
3 years	-0.029	-0.147^{+}	-0.143^{+}	-0.090	-0.182	-0.122^{+}
	(0.063)	(0.075)	(0.075)	(0.099)	(0.146)	(0.066)
Pre-reform baseline (1 year)	0.068	0.228	0.219	0.129	0.154	0.194
Observations	16226	50685	45297	21614	8113	58798

Standard errors in parentheses. $^{+}$ $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Note: Table shows estimates of the effect of DNA profiling on subsequent crime. Separate estimates for subgroups are obtained by interacting the reform dummy with subgroup dummies. Subgroups in Panel A are first time offenders (sampling charge is their first charge) and redivists (has between1-10 prior charges). Subgroups in Panel B are offenders aged 18-23 and 24-30 at the time of the sampling charge. Subgroups in Panel C are those who have at least one child at the time of sampling and those that have none. Depending on the panel covariates include age, immigrant background, has children, single, years of education, gross income, employment status, number of prior charges, crime type dummies and month fixed effects. Standard errors are clustered by personal id number. Source: Own calculations based on Data from Statistics Denmark and the National Police.

Table A-7: Difference in difference estimates of the reform expanding DNA profiling on subsequent accumulated probability of conviction and number of convictions

	P(convicted)	**# convictions**
1 year	-0.018*	-0.019+
	(0.007)	(0.010)
2 years	-0.022*	-0.028+
	(0.009)	(0.017)
3 years	-0.024*	-0.038+
	(0.010)	(0.022)
Observations	50267	50267

Standard errors in parentheses. + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Note: Table shows Difference in Difference estimates of the reform. We estimate this as:
$y_{it} = \alpha + \gamma_1 \mathbf{1}[post] + \gamma_2 \mathbf{1}[Treatment_i] + \gamma_3 \mathbf{1}[post_i] * \mathbf{1}[Treatment_i] + \epsilon_{it}$
where γ_3 is the *DiD* estimate presented in the table.

Table A-8: Reduced form estimates predicting probability of convictions and the number of convictions from timing of initial charge in placebo samples

	P(convicted)	**# convictions**
2002, placebo reform	0.002	0.005
	(0.007)	(0.011)
2003, placebo reform	0.007	0.004
	(0.007)	(0.011)
2004, placebo reform	0.004	0.006
	(0.007)	(0.011)
2005, actual reform	-0.022***	-0.032**
	(0.007)	(0.010)
2006, placebo reform	-0.010	-0.007
	(0.006)	(0.009)

Standard errors in parentheses + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$ Note: Table shows reduced form estimates from regressing subsequent convictions on a "after-reform"-dummy (along with running variables, covariates and month FE) in a series of placebo samples. The placebo samples mirrors the original sample except that the reform is artificially set to occur in e.g. 2002 instead of 2005, and as in the original samples the sampling window is defined as +/-24 months around the reform (except from June-September in the reform year). Standard errors are clustered on personal identification number. Source: Own calculations based on Data from Statistics Denmark and the National Police

Table A-9: Effects of DNA profiling, including summer months

	Full sample	First charge	Recidivist	Aged 18-23	Aged 24-30	Child	No child
P(convicted), all crime							
1 year	-0.037	-0.041	-0.040	-0.077*	0.071	0.068	-0.050
	(0.031)	(0.042)	(0.038)	(0.038)	(0.055)	(0.089)	(0.033)
2 years	-0.063+	-0.099+	-0.058	-0.095*	0.021	-0.063	-0.062
	(0.038)	(0.059)	(0.046)	(0.045)	(0.072)	(0.114)	(0.040)
3 years	-0.042	-0.032	-0.049	-0.057	-0.008	-0.001	-0.046
	(0.039)	(0.065)	(0.047)	(0.046)	(0.077)	(0.119)	(0.041)
# convictions, all crime							
1 year	-0.075	-0.020	-0.094	-0.136*	0.093	0.126	-0.099*
	(0.047)	(0.048)	(0.058)	(0.057)	(0.083)	(0.148)	(0.050)
2 years	-0.147+	-0.042	-0.183+	-0.197*	-0.017	0.006	-0.164*
	(0.076)	(0.082)	(0.094)	(0.093)	(0.128)	(0.200)	(0.082)
3 years	-0.123	-0.019	-0.162	-0.137	0.104	0.069	-0.144
	(0.097)	(0.107)	(0.121)	(0.121)	(0.159)	(0.251)	(0.105)
First stage on probability of DNA profiling:							
Charged post reform	0.212***						
	(0.006)						

Standard errors in parentheses. + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Note: Table shows estimates of the effect of DNA profiling on subsequent crime including the months that are excluded in the main analysis. Covariates include age, immigrant background, has children, single, years of education, gross income, employment status, number of prior charges, crime type dummies and month fixed effects. Observations: 72,338. Standard errors are clustered by personal id number. Source: Own calculations based on Data from Statistics Denmark and the National Police.

Table A-10: Effects of DNA profiling on subsequent convictions (accumulated) by different bandwidth specifications

	P(convicted)				**# convictions**			
	BW:12	BW:18	BW:24	BW:30	BW:12	BW:18	BW:24	BW:30
A: All convictions								
1 year	-0.054^{+}	-0.064**	-0.065***	-0.074***	-0.087*	-0.106***	-0.093**	-0.108***
	(0.030)	(0.022)	(0.019)	(0.017)	(0.042)	(0.032)	(0.029)	(0.025)
2 years	-0.041	-0.063*	-0.075**	-0.099***	-0.107	-0.164**	-0.163***	-0.212***
	(0.037)	(0.027)	(0.024)	(0.021)	(0.068)	(0.052)	(0.048)	(0.044)
3 years	-0.040	-0.061*	-0.047^{+}	-0.070**	-0.118	-0.175**	-0.129*	-0.183**
	(0.038)	(0.028)	(0.025)	(0.022)	(0.088)	(0.067)	(0.061)	(0.057)
Observations	33509	50245	66911	83147	33509	50245	66911	83147

Standard errors in parentheses + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$ Note: Table shows 2SLS estimates of regressing subsequent crime on DNA profiling (instrumented by timing of initial charge - before/after reform) by different bandwidth specifications. Covariates include age, immigrant background, has children, single, years of education, gross income, employment status, number of prior charges, crime type dummies and month fixed effects. Standard errors are clustered by personal identification number. Source: Own calculations based on Data from Statistics Denmark and the National Police.

Table A-11: Effects of DNA profiling on subsequent accumulated number of convictions using different running variable specifications

Years	(1)	(2)
1 year	-0.093**	-0.094*
	(0.029)	(0.041)
2 years	-0.163***	-0.125+
	(0.048)	(0.067)
3 years	-0.129*	-0.168+
	(0.061)	(0.087)
Observations	66911	66911
Running variables:		
Linear	X	X
Quadratic		X

Standard errors in parentheses. + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Note: Table shows 2SLS estimates of regressing subsequent crime on DNA registration (instrumented by timing of initial charge - before/after reform) with the baseline specification of the running variable (linear, but flexible on each side or the reform) from Table 7, and a more flexible quadratic running variable (also flexible on each side of the reform). Covariates include age, immigrant background, has children, single, years of education, gross income, employment status, number of prior charges, crime type dummies and month fixed effects. Standard errors are clustered by personal identification number. Source: Own calculations based on Data from Statistics Denmark and the National Police.

Table A-12: Effects of DNA profiling on subsequent convictions - adjusted for time spent incarcerated

	# **convictions**		
	Adj. no cap	Adj. cap=0.5	Adj. cap=0.75
1 year	-0.098**	-0.104**	-0.101**
	(0.032)	(0.032)	(0.032)
2 years	-0.185***	-0.187***	-0.186***
	(0.053)	(0.053)	(0.053)
3 years	-0.155*	-0.156*	-0.156*
	(0.068)	(0.068)	(0.068)
Observations	66908	66911	66911

Standard errors in parentheses + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$ Note: Table shows IV estimates of regressing subsequent convictions on DNA profiling (instrumented by timing of initial charge - before/after reform). Number of subsequent convictions have been divided by the proportion of the follow up period not spent incarcerated with different caps on the maximum proportion of time spent incarcerated. Covariates include age, immigrant background, has children, single, years of education, gross income, employment status, number of prior charges, crime type dummies, and month fixed effects. Standard errors are clustered by personal identification number. Source: Own calculation based on Data from Statistics Denmark.

Table A-13: Effects of DNA registration on subsequent convictions by time it takes to solve crime

	Panel A	**Panel B**		**Panel C**		**Panel D**		**Panel E**		**Panel F**	
	Full sample	Criminal trajectory		Age at charge		Parenthood		Initially charged for		Subsequently convicted of	
		First charge	Recidivist	18-23	24-30	Child	No child	prop. crime	viol. crime	prop. crime	viol. crime
P(convicted), solved fast											
1 year	-0.057**	-0.044^{+}	-0.060**	-0.079***	0.000	-0.058	-0.057**	-0.051^{+}	-0.058**	-0.033*	-0.025*
	(0.018)	(0.022)	(0.022)	(0.022)	(0.030)	(0.047)	(0.020)	(0.027)	(0.020)	(0.015)	(0.012)
2 years	-0.084***	-0.081*	-0.083**	-0.094***	-0.060	-0.177**	-0.073**	-0.084*	-0.082**	-0.047*	-0.030^{+}
	(0.023)	(0.032)	(0.027)	(0.027)	(0.040)	(0.062)	(0.024)	(0.034)	(0.026)	(0.020)	(0.016)
3 years	-0.067**	-0.055	-0.068*	-0.067*	-0.069	-0.188**	-0.053*	-0.060^{+}	-0.074**	-0.044*	-0.029
	(0.024)	(0.036)	(0.028)	(0.028)	(0.043)	(0.066)	(0.025)	(0.036)	(0.028)	(0.021)	(0.018)
P(convicted), solved slow											
1 year	-0.016	-0.004	-0.018	-0.026*	0.014	0.022	-0.020^{+}	-0.013	-0.012	-0.006	-0.006
	(0.010)	(0.011)	(0.012)	(0.012)	(0.019)	(0.027)	(0.011)	(0.016)	(0.010)	(0.009)	(0.005)
2 years	-0.030^{+}	-0.007	-0.035^{+}	-0.039*	-0.008	0.009	-0.035*	-0.038	-0.025	-0.018	-0.009
	(0.016)	(0.019)	(0.019)	(0.020)	(0.029)	(0.045)	(0.017)	(0.025)	(0.016)	(0.014)	(0.008)
3 years	-0.006	0.016	-0.010	-0.008	-0.000	0.050	-0.013	0.003	-0.011	-0.010	-0.006
	(0.019)	(0.023)	(0.023)	(0.023)	(0.033)	(0.053)	(0.020)	(0.029)	(0.020)	(0.016)	(0.011)
# convictions, solved fast											
1 year	-0.076**	-0.034	-0.085**	-0.101**	-0.009	-0.080	-0.075**	-0.073^{+}	-0.065**	-0.044*	-0.029*
	(0.026)	(0.025)	(0.032)	(0.032)	(0.041)	(0.063)	(0.028)	(0.040)	(0.025)	(0.021)	(0.013)
2 years	-0.124**	-0.061	-0.137**	-0.141**	-0.078	-0.204*	-0.114**	-0.122^{+}	-0.101**	-0.060^{+}	-0.032
	(0.041)	(0.042)	(0.050)	(0.050)	(0.067)	(0.099)	(0.044)	(0.063)	(0.039)	(0.033)	(0.020)
3 years	-0.127*	-0.046	-0.141*	-0.140*	-0.089	-0.216^{+}	-0.115*	-0.112	-0.122*	-0.052	-0.033
	(0.051)	(0.054)	(0.062)	(0.062)	(0.084)	(0.124)	(0.055)	(0.079)	(0.049)	(0.040)	(0.024)
# convictions, solved slow											
1 year	-0.017^{+}	-0.002	-0.021^{+}	-0.028*	0.013	0.017	-0.022^{+}	-0.016	-0.012	-0.007	-0.006
	(0.010)	(0.011)	(0.013)	(0.012)	(0.020)	(0.028)	(0.011)	(0.016)	(0.010)	(0.009)	(0.005)
2 years	-0.039*	-0.005	-0.046*	-0.048*	-0.015	0.010	-0.045*	-0.049^{+}	-0.028	-0.028^{+}	-0.009
	(0.019)	(0.020)	(0.023)	(0.024)	(0.031)	(0.049)	(0.021)	(0.030)	(0.019)	(0.016)	(0.008)
3 years	-0.002	0.017	0.005	-0.003	-0.001	0.033	-0.007	0.016	-0.007	-0.011	0.006
	(0.026)	(0.027)	(0.031)	(0.032)	(0.039)	(0.065)	(0.028)	(0.040)	(0.025)	(0.021)	(0.011)

Standard errors in parentheses. $^{+}$ p<0.10, * p<0.05, ** p<0.01, *** p<0.001. Note: Table shows 2SLS estimates of regressing subsequent crime on DNA registration by time from date of crime to charge (solved fast < 3 weeks, solved slowly $\geq$ three weeks). The results are presented for the full sample (Panel A), by offender characteristics (Panels B-E), and by crime type (Panel F). Covariates include age, immigrant background, has children, single, years of education, gross income, employment status, number of prior charges, crime type dummies and month fixed effects. Standard errors are clustered by personal identification number. Source: Own calculations based on Data from Statistics Denmark and the National Police.

Table A-14: Effects of DNA profiling on subsequent accumulated probability of conviction and number of convictions, 2 week and 3 week cut-offs

	P(convicted)				**# convictions**			
	Fast charge		Slow charge		Fast charge		Slow charge	
	2w	3w	2w	3w	2w	3w	2w	3w
Years								
Main results								
1 year	-0.055**	-0.057**	-0.017	-0.016	-0.074**	-0.076**	-0.020	-0.017+
	(0.018)	(0.018)	(0.11)	(0.010)	(0.025)	(0.026)	(0.012)	(0.010)
2 years	-0.077***	-0.084***	-0.040*	-0.030+	-0.111**	-0.124**	-0.051*	-0.039*
	(0.023)	(0.023)	(0.018)	(0.016)	(0.039)	(0.041)	(0.022)	(0.019)
3 years	-0.065**	-0.067**	-0.016	-0.006	-0.113*	-0.127*	-0.016	-0.002
	(0.024)	(0.024)	(0.020)	(0.019)	(0.049)	(0.051)	(0.029)	(0.026)
Observations	66911	66911	66911	66911	66911	66911	66911	66911
Pre-reform baseline, 1 year								
Main outcomes	0.125	0.132	0.037	0.029	0.149	0.158	0.040	0.031

Standard errors in parentheses. + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Note: Table shows 2SLS estimates of regressing subsequent crime on DNA registration (instrumented by timing of initial charge - before/after reform). Covariates include age, immigrant background, has children, single, years of education, gross income, employment status, number of prior charges, crime type dummies and month fixed effects. Standard errors are clustered by personal identification number. Source: Own calculations based on Data from Statistics Denmark and the National Police.

Table A-15: Deterrence and detection effects on subsequent new crime. 2 week cut-off

	Deterrence effect Δ		**Detection effect δ**		Clearance rate p	Clearance rate	Elasticity of #new crimes
	P(new crime)	#new crimes	P(new crime)	#new crimes		w. 3 weeks $p\pi$	with respect to p
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A:Any Crime							
3 years	-0.301 ***	-0.507 ***	0.033 +	0.071 **	0.399	0.228	-2.9
B: Property							
3 years	-0.266 **	-0.264 +	0.023	0.017	0.305	0.159	-4.8
C: Violence							
3 years	-0.055 +	-0.061 *	0.018 +	0.021 +	0.820	0.549	-2.4
Pre-reform baseline / clearance rate ($\bar{p}$), 3 year							
	P(new crime)	# new crimes					
Any Crime	0.939	1.633					
Property	0.780	1.228					
Violence	0.172	0.216					

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 Note: Table shows estimates of deterrence and detection effects calculated on the basis of IV-estimation (including covariates and month FE) from 100 bootstrapped samples. Clearing rates were calculated on the basis of all charges and all reported crime in 2005. In these measures we excluded crime types such as bicycle theft which is heavily reported (often for insurance purposes) but rarely solved and leading to a charge (<10% of the time) in order not to inflate estimates by an extremely low clearance rate. The fraction of crimes solved within 2 weeks is 0.572 overall, 0.520 for property crimes, and 0.670 for violent crimes. Source: Own calculations based on Data from Statistics Denmark and the National Police.

Table A-16: Effects of DNA profiling on subsequent accumulated probability of conviction and number of convictions, main results and excluding low clearance crimes

	P(convicted)			**# convictions**		
	All	Fast	Slow	All	Fast	Slow
Years	(1)	(2)	(3)	(4)	(5)	(6)
Main results						
1 year	-0.065***	-0.057**	-0.016	-0.093**	-0.076**	-0.017^{+}
	(0.019)	(0.018)	(0.010)	(0.029)	(0.026)	(0.010)
2 years	-0.075**	-0.084***	-0.030^{+}	-0.163***	-0.124**	-0.039*
	(0.024)	(0.023)	(0.016)	(0.048)	(0.041)	(0.019)
3 years	-0.047^{+}	-0.067**	-0.006	-0.129*	-0.127*	-0.002
	(0.025)	(0.024)	(0.019)	(0.061)	(0.051)	(0.026)
Observations	66911	66911	66911	66911	66911	66911
Excluding low clearance crimes						
1 year	-0.071***	-0.065***	-0.016	-0.107***	-0.089***	-0.017^{+}
	(0.019)	(0.018)	(0.010)	(0.027)	(0.024)	(0.010)
2 years	-0.076**	-0.087***	-0.030^{+}	-0.161***	-0.122**	-0.039*
	(0.024)	(0.023)	(0.016)	(0.044)	(0.037)	(0.019)
3 years	-0.061*	-0.081***	-0.006	-0.138*	-0.135**	-0.002
	(0.025)	(0.024)	(0.019)	(0.057)	(0.046)	(0.026)
Observations	66911	66911	66911	66911	66911	66911
Pre-reform baseline, 1 year						
Main outcomes	0.153	0.132	0.029	0.189	0.158	0.031
Excluding low clearance crimes	0.141	0.122	0.029	0.174	0.144	0.031

Standard errors in parentheses. $^{+}$ $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Note: Table shows 2SLS estimates of regressing subsequent crime on DNA registration (instrumented by timing of initial charge - before/after reform).The first panel reproduces our main results, but the second panel excludes crime types such as bicycle theft which is heavily reported (often for insurance purposes) but rarely solved and leading to a charge (<10% of the time), which corresponds to the crimes included when calculating the overall clearance rates. Covariates include age, immigrant background, has children, single, years of education, gross income, employment status, number of prior charges, crime type dummies and month fixed effects. Standard errors are clustered by personal identification number. Source: Own calculations based on Data from Statistics Denmark and the National Police.

Table A-17: Test for external validity of LATE estimates

	P(convicted)			**# convictions**		
	All	Fast	Slow	All	Fast	Slow
Years	(1)	(2)	(3)	(4)	(5)	(6)
1 year	p<0.001	p<0.001	p<0.001	p<0.001	p=0.151	p<0.001
2 years	p<0.001	p<0.001	p=0.630	p=0.013	p=0.686	p<0.001
3 years	p=0.094	p<0.001	p<0.001	p<0.001	p<0.001	p<0.666

Note: Table shows tests for external validity of the IV estimates reported in Table 7 following Brinch, Mogstad and Wiswall (2017):
$E(Y|DNA = 0, Z = 1) - E(Y|DNA = 0, Z = 0) =$
$E(Y|DNA = 1, Z = 1) - E(Y|DNA = 1, Z = 0)$
in the limit around the reform Z. The naught is that treatment effects are homogeneous and the alternative is that treatment effects are heterogeneous across the two treatment margins $Z = 0$ (where approximately 5% are included in the DNA register) and $Z = 1$ (where approximately 40% are included in the DNA register), see Figure 1a. Intuitively, this test correponds to testing whether there would be a significant slope if we estimated Marginal Treatment Effects between the two points of variation.

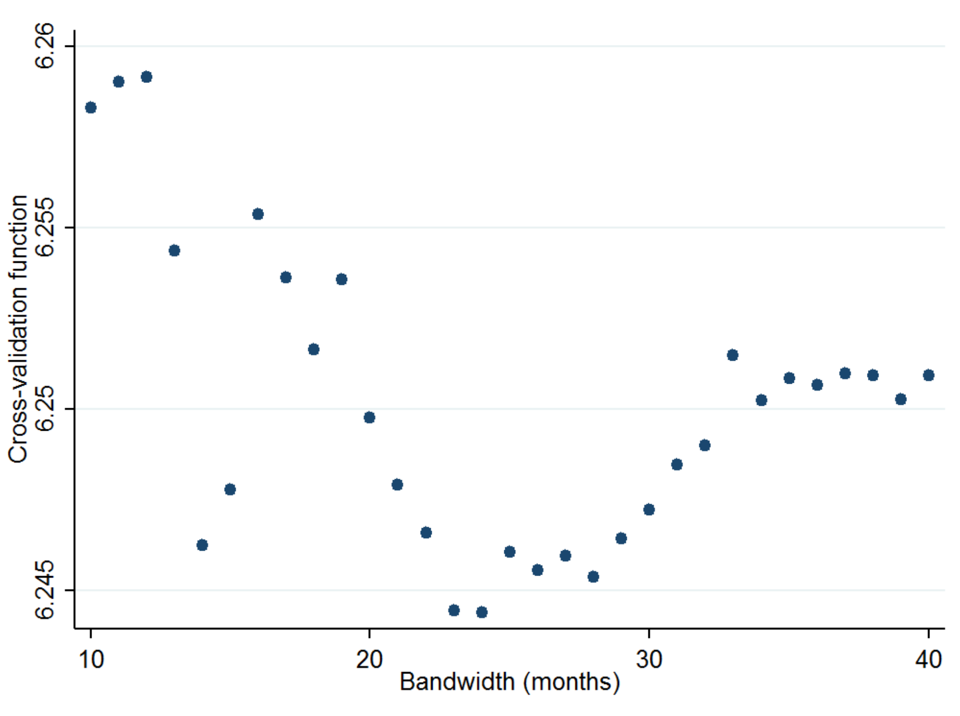


Figure A-1: Cross-validation function by bandwidth

Note: The figures shows the cross-validation (CV) function plotted against different bandwidths. The CV function is calculated in two steps (as described in Lee and Lemieux (2010) and Ludwig and Miller (2005)). First, we estimated the reduced form estimates with a dummy variable indicating before/after reform and running variables measuring months before or after the reform (+ covariates), but leaving out observations in the 1-3 month preceding and following the reform. Second, we used the estimates to predict the outcome for the observations in the excluded window around the reform, and calculate the mean prediction error for each outcome. The prediction errors (CV functions) were then aggregated across the outcomes and across 1-3 month prediction windows. This was done for bandwidths ranging from 10 to 40 months before/after the reform. Source: Own calculations based on Data from Statistics Denmark and the National Police.

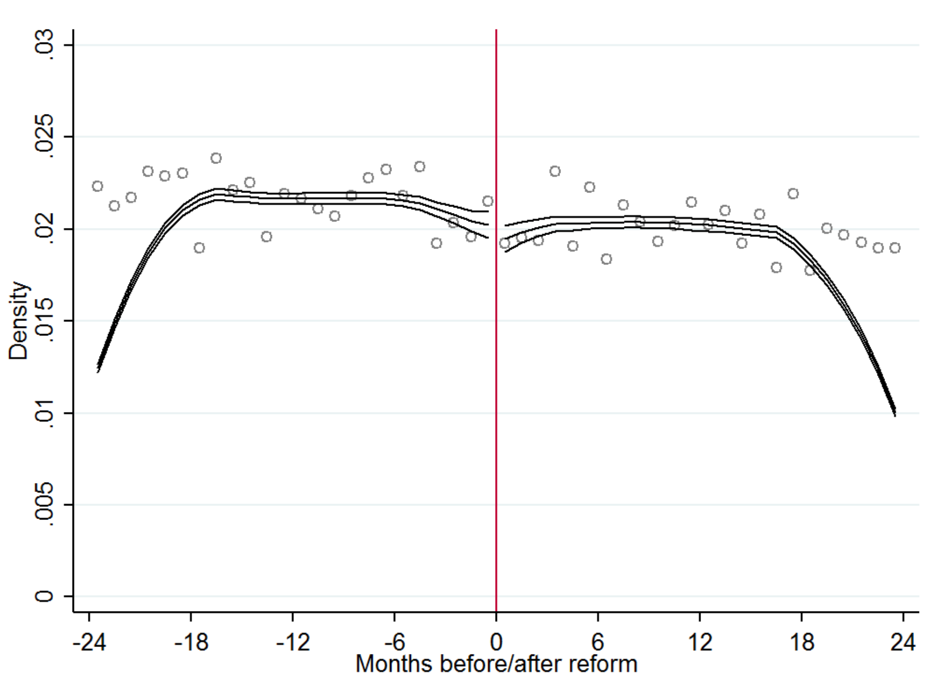


Figure A-2: McCrary density test

Note: Figure shows density before and after reform in bins of one month. A McCrary test for discontinuity in density (with default bandwidth) gives a theta of -0.041 with standard error of 0.030 and a t-value of -1.339. Source: Own calculations based on Data from Statistics Denmark and the National Police.

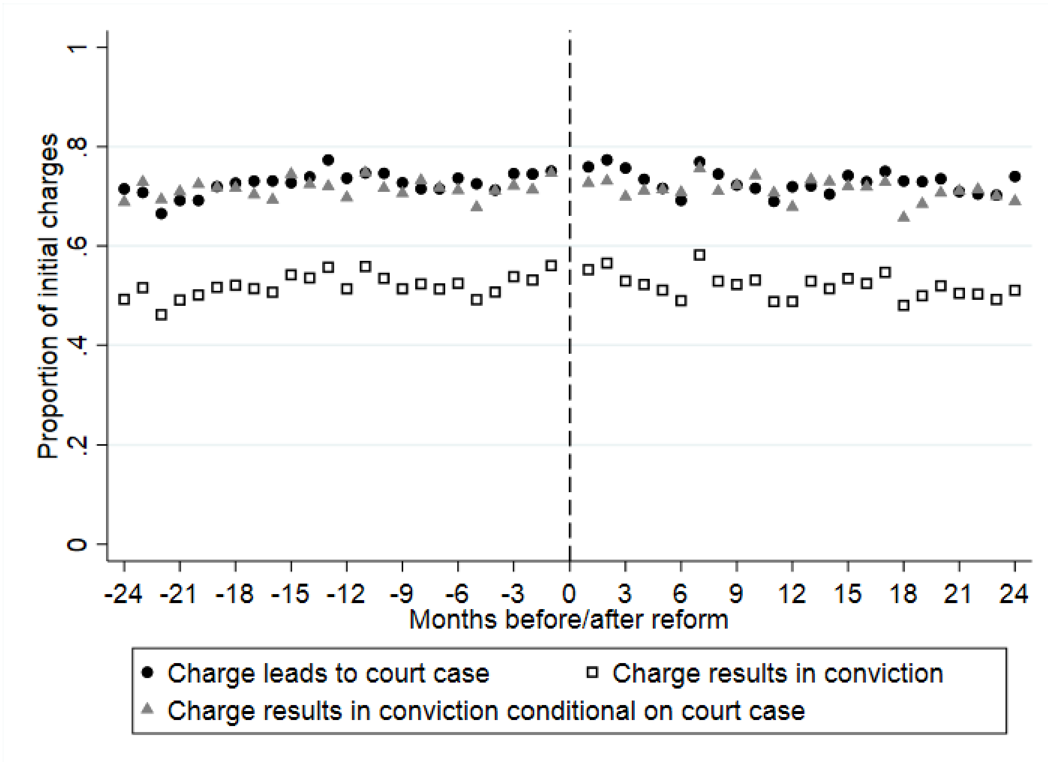


Figure A-3: Probability of charge leading to a court case and a conviction by date of charge
Note: Figure shows, by month of charge relative to the reform, the likelihood of charges leading to a court case, charges leading to a conviction, and charges leading to a conviction conditional on going to court.

(a) All crime

(b) Burglaries

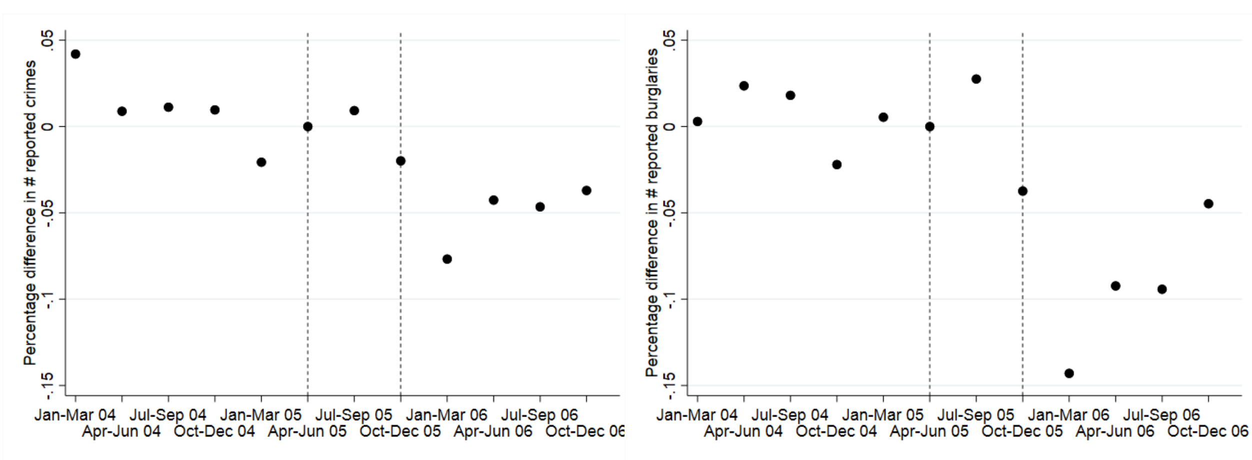
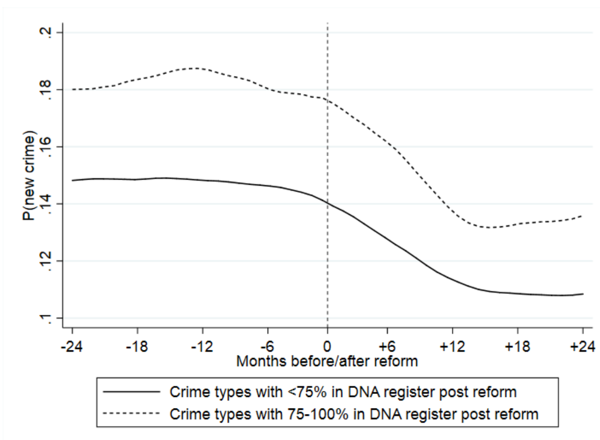


Figure A-4: Reported crime relative to April-June 2005
Note: Figure shows the number of reported crimes (/burglaries) relative to April-June 2005 level.

(a) P(conviction), 1 year, level



(b) P(conviction), 1 year, demeaned relative to pre-reform level

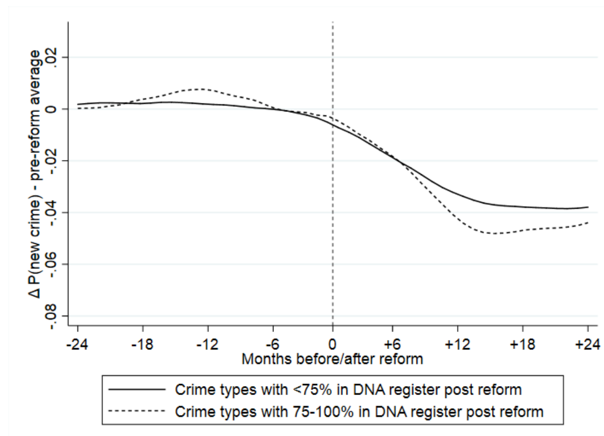


Figure A-5: Crime levels before and after the reform for the Difference in Difference control and treament groups

Note: Figure shows the probability of receiving a conviction for a new crime within the first year after an initial charge for charges pressed 24 months before the reform until 24 months after the reform. The crime levels are separated by treatment status, where the treatment group are those with crime types where at least 75% lead to DNA registration in the post reform period, and the control group are those with crime types where less than 75% were added to the database in the post reform period. The crime types where DNA registration was used pre-reform (homicide, rape, attempted murder, and very serious violence) are excluded from the figure as these groups' DNA registration was unaffected by the reform. Figure A shows the overall crime levels, Figure B shows crime demeaned such that pre-reform crime is equal to zero.

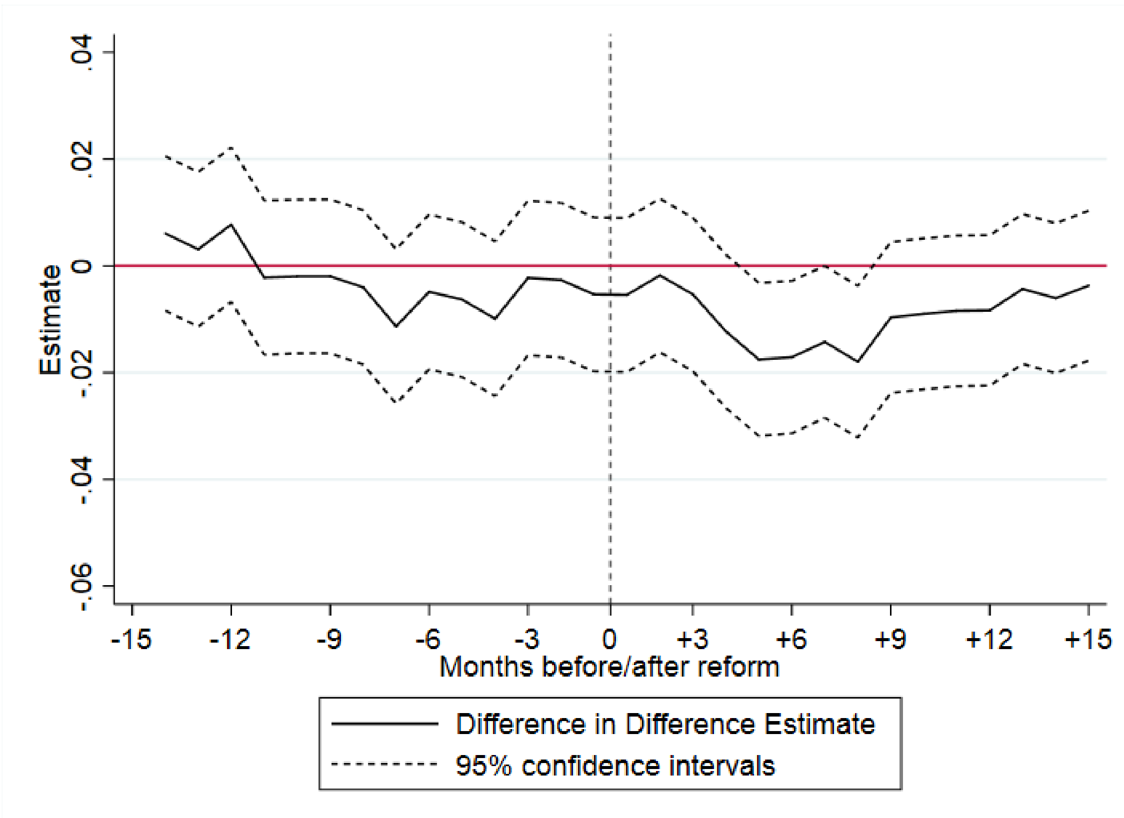
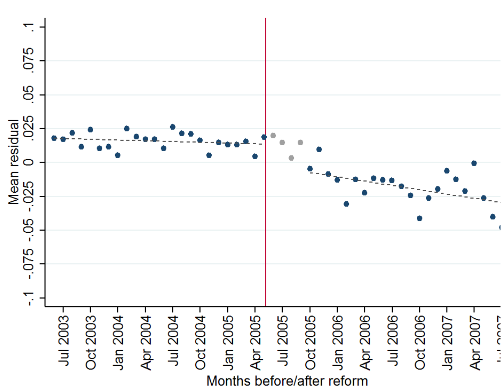
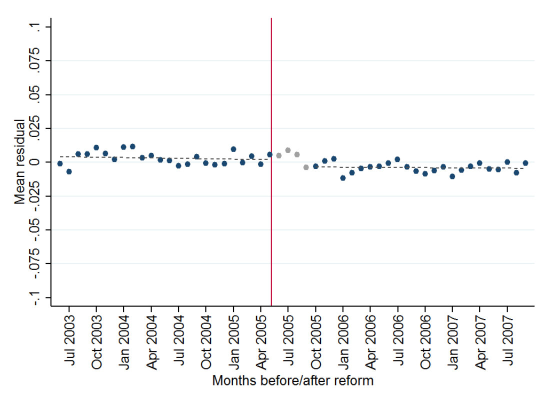


Figure A-6: Difference in Difference estimates using different cutoffs
Note: Figure shows Difference in Difference estimates on the probability of receiving a conviction for a new crime within the first year after an initial charge varying the separation of pre and post periods from 15 months before the reform until 15 months after the reform.

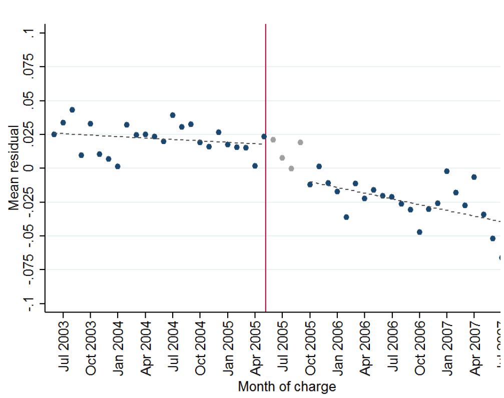
(a) P(conviction w. fast charge), 1 year



(b) P(conviction w. slow charge), 1 year



(c) # convictions w. fast charge, 1 year



(d) # convictions w. slow charge, 1 year

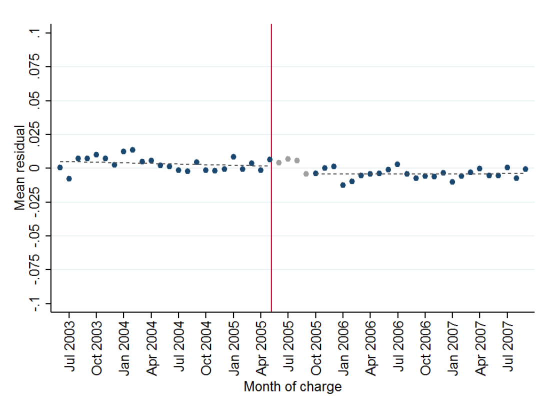


Figure A-7: Monthly means of crime outcomes around the timing of the reform, by timing between date of crime and date of charge

Note: Figures show monthly means of crime outcomes within one year by time it takes to charge the offender for crime. Figures A and B show the probability of receiving at least one conviction and Figures C and D show monthly means number of convictions. Figures A and C show means for charges filed within three weeks from the date of crime, and Figures B and D show results for crime charges filed after three weeks from the date of crime. We condition on covariates in all figures. Therefore the figures show deviations around the conditional sample mean and not absolute levels. Source: Own calculations based on Data from Statistics Denmark and the National Police.

(a) Difference in crime with DNA registration (Y^1) for always takes and compliers

(b) Difference in crime without DNA registration (Y^0) for never takes and compliers

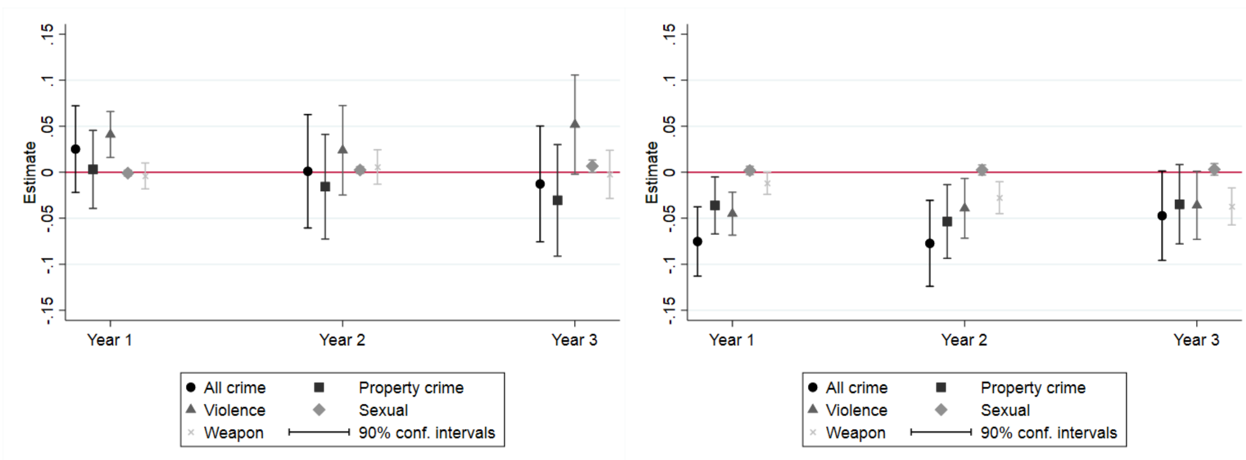


Figure A-8: Differences in crime with and without DNA registration by compliance-status

Note: Figure shows estimated differences between Y^0 (i.e. crime for offenders who are not in the DNA database) for never-takers and compliers, and Y^1 (i.e. crime for offenders who are in the DNA database) for always-takers and compliers using the specification outlined in Black et al. (2015).

B Online Appendix: Framework extensions

The effects of DNA databases on the deterrence and detection of offenders

Anne Sofie Tegner Anker, Jennifer L. Doleac, and Rasmus Landersø

This section first derives the equations identifying the deterrence effect, the detection effect, and the elasticity of crime with respect to detection probability (Equation 9) presented in Section V.B. This section subsequently expands this framework and relaxes the assumptions on (i) invariance of the detection probability $\bar{p}$ across potentially fast and slow solved crimes, and (ii) homogenous deterrence effects across potentially fast and slow solved crimes.

B.1 Baseline identification of deterrence and detection effects

We identify the effects by exploiting the Danish register data. The data both include when offenders are charged for a crime and the exact dates of crime. We divide observed crime $\tilde{y}_i$ into two categories: crime that is solved fast, $\tilde{y}_i^F$, and crime that is solved slowly, $\tilde{y}_i^S$.

The former, $\tilde{y}_i^F$, denotes crime solved within three weeks from the date of crime, before any DNA evidence from the crime scene could have been processed. The latter, $\tilde{y}_i^S$, denotes crime solved after three weeks from the date of crime, at which point DNA evidence could have been processed and been used in the investigation. Hence, changes in crime solved within three weeks from the date of the crime will only capture the deterrence effect, while changes in crime solved more slowly will be a composite of both the deterrence and detection effects (that is, the combined effects on the likelihood that a crime occurs and the likelihood that we observe it in the data). In our main set of results, which we will present in Section IV.B, we will present estimates of DNA registration separately for all observed crime $\tilde{y}_i$, cases solved fast $\tilde{y}_i^F$, and cases solved slowly $\tilde{y}_i^S$, thereby making the different impacts of the deterrence and detection effects explicit. All estimates from $\tilde{y}_i$, $\tilde{y}_i^F$, and $\tilde{y}_i^S$ are attenuated as only a fraction of crime is linked to offenders. However, as estimates using $\tilde{y}_i^F$ do not contain a detection effect, they are not biased upwards and they, therefore, provide a lower bound of the deterrence effect.

We assume that the baseline clearance rate of crime without the DNA database $\bar{p}$ occurs at a fixed rate and that it is uniform and invariant with offender characteristics that are not captured by the different crime types (see footnote 29 in the main text for a further description of this assumption). Thereby, we express the fraction of solved crime that occurs within three weeks from the date of crime as $\pi\bar{p}$ both before and after the expansion of the DNA database. Therefore:

$$\tilde{y}_i^F = \pi\bar{p}y_i,$$

$$\tilde{y}_i^S = ((1-\pi)\bar{p} + \gamma DNA_i)y_i$$

DNA registration's effect on crime solved within three weeks using the reform as an IV equals:

$$\begin{aligned} \beta_F^{IV} &= \pi\bar{p} * E(\Delta) \Rightarrow \\ E(\Delta) &= (\beta_F^{IV})/(\pi\bar{p}), \end{aligned} \tag{B.1}$$

which is the deterrence effect. As we observe all crime reports and the share leading to a charge (the clearance rate) within three weeks from the crime date, we know $\pi\bar{p}$ and may estimate $E(\Delta)$. Turning to the effect on crime solved after three weeks from the crime date:

$$\beta_S^{IV} = E[\gamma DNA_i * y_i^1 + (1-\pi)\bar{p} * \Delta]$$

By subtracting the former estimate β_F^{IV} multiplied by $(1-\pi)/\pi$ from β_S^{IV} we arrive at:

$$\begin{aligned} \beta_S^{IV} - \beta_F^{IV} * (1-\pi)/\pi &= E[\gamma DNA_i * y_i^1 + (1-\pi)\bar{p} * \Delta] - \pi\bar{p} * E(\Delta) * ((1-\pi))/\pi \\ &= E[\gamma DNA_i * y_i^1] \\ &= E(\delta) \end{aligned} \tag{B.2}$$

which is the detection effect, and the elasticity of crime with respect to detection probability:

$$
\begin{aligned}
E[\epsilon] &= \bar{p} * [(\beta_F^{IV})/(\pi\bar{p})]/[\beta_S^{IV} - \beta_F^{IV} * (1-\pi)/\pi] \\
&= \beta_F^{IV}/[\pi * (\beta_S^{IV} + \beta_F^{IV}) - \beta_F^{IV}] \\
&= \beta_F^{IV}/(\pi\beta^{IV} - \beta_F^{IV})
\end{aligned}
\tag{B.3}
$$

B.2 Heterogenous baseline detection probability

In our data we observe the fraction of all crime where the offender is caught, and we label this $\bar{p}$. In the baseline framework we assume that $\bar{p}$ is invariant across the time it takes to apprehend the offender. However, it is plausible that the underlying clearance rate for the crimes that are potentially solved fast and slow, respectively, differ. If, for example, fast solved crimes are "low hanging fruits" committed by less skilled criminals and slow solved crimes are committed by more skilled criminals (note that we distinguish between (i) fast and slow solved crimes, and (ii) *potentially* fast and slow solved crimes. The former refers to what we actually observe in the data, the latter to underlying different types of crime).

Therefore, we now expand the framework to allow for two different clearance rates $\bar{p}^F$ for fast solved crime and $\bar{p}^S$ for slow solved crime. As we will show below, the results presented in the main paper are a weighted average between the resulting detection and deterrence effects for potentially fast and slow solved crimes. If fast solved crimes are committed by less skilled criminals and slow solved crimes are committed by more skilled criminals, then the elasticity of crime with respect to the detection probability will be larger for fast solved crimes, because potentially fast solved crime is relatively more responsive to the DNA profilling.

The challenge is that we only observe the fraction of all crime that is solved, and whether this was within three weeks from the date of crime. If potentially fast and slow solved crime, y^F and y^S, are fundamentally different, we cannot separately determine the fraction of y^F and y^S that are not solved. Hence, while we observe $\bar{p}$ for all crime, we cannot distinguish between the underlying fractions of fast and slow solved crime (defined by π and $1-\pi$), and the specific heterogenous clearance rates $\bar{p}^F$ an $\bar{p}^S$. We can only observe that a given fraction of all cases leads to a fast charge, $\pi * \bar{p}^F$, and that another fraction of all cases leads to a slow charge, $(1-\pi) * \bar{p}^S$ where the overall clearance rate is the sum of the two:

$$\bar{p} = \pi * \bar{p}^F + (1-\pi) * \bar{p}^S \tag{B.4}$$

Below we show that heterogenous clearance rates do not change the overall elasticity of crime with respect to the clearance rate. In fact, the overall elasticity is simply a weighted average between the elasticity of fast solved and slow solved crime.

As a starting point, we will revisit how we measure one of the central moments in the baseline framework, the fraction of fast solved crime π. We measure this as the fraction of crime that is solved within three weeks from the date of the crime relative to all crime that is solved. Hence, this fraction implicitly involves the clearance rate. In the case with an invariant clearance rate $\bar{p}$ this will equal $\pi\bar{p}/\bar{p} = \pi$. Yet, if the underlying clearance rate differs across time it takes to solve a crime, then we actually use as π the term $\pi\bar{p}^F/\bar{p}$.

Next, we will expand Equation 5 with counterfactual crime with (y_1) and without (y_0) a DNA database to allow for differences between potentially fast and slow solved crime. Observed fast crime y^F and slow crime y^S are defined as:

$$\begin{aligned}
\tilde{y}_0^F &= \pi\bar{p}^F * y_0 \\
\tilde{y}_1^F &= \pi\bar{p}^F * y_1 \\
\tilde{y}_0^S &= (1-\pi)\bar{p}^S * y_0 \\
\tilde{y}_1^S &= ((1-\pi)\bar{p}^S + \gamma DNA) * y_1
\end{aligned} \tag{B.5}$$

DNA only enter observed slow solved crime, as fast solved crime is always solved before DNA evidence is available. Therefore:

$$\begin{aligned}
\tilde{y}_1^F - \tilde{y}_0^F &= \pi\bar{p}^F * \Delta, \\
\tilde{y}_1^S - \tilde{y}_0^S &= (1-\pi)\bar{p}^S * \Delta + \gamma DNA * y_1
\end{aligned}$$

From this we see that the deterrence effect Δ is identified from the fast solved crime, just as in the baseline framework where we had an invariant clearance rate:

$$\Delta = \frac{\tilde{y}_1^F - \tilde{y}_0^F}{\pi \bar{p}^F} \implies$$
$$E(\Delta) = \frac{\beta_F^{IV}}{\pi \bar{p}^F}$$

What has changed, however, is the identification of the detection effect δ:

$$\tilde{y}_1^S - \tilde{y}_0^S = (1-\pi)\bar{p}^S * \Delta + \gamma DNA_i * y_i^1 \implies$$
$$\tilde{y}_1^S - \tilde{y}_0^S - (1-\pi)\bar{p}^S * \Delta = \gamma DNA_i * y_i^1$$
$$= \delta$$

Inserting the result for the clearance rate from above yields:

$$E(\delta) = \beta_S^{IV} - \frac{1-\pi}{\pi} \frac{\bar{p}^S}{\bar{p}^F} * \beta_F^{IV}$$

This is identical to the baseline expression except for the fraction $\bar{p}^S/\bar{p}^F$, which for the homogenous $\bar{p}$ would have been cancelled out. Therefore, we can express the corresponding elasticities of crime with respect to the detection probability as done in Equation B.3 in the baseline framework:

$$\begin{gathered}
\epsilon^F = \bar{p}^F * \frac{\Delta}{\delta} \qquad\qquad \epsilon^S = \bar{p}^S * \frac{\Delta}{\delta} \\
\Downarrow \\
E(\epsilon^F) = \bar{p}^F \frac{\beta_F^{IV}}{\pi \bar{p}^F \beta^{IV} - \bar{p}\beta_F^{IV}} \qquad E(\epsilon^S) = \bar{p}^S \frac{\beta_F^{IV}}{\pi \bar{p}^F \beta^{IV} - \bar{p}\beta_F^{IV}}
\end{gathered} \tag{B.6}$$

From Equation B.6, it also follows that the weighted average between the two elasticities $\pi\epsilon^F + (1-\pi)\epsilon^S$ equals the overall elasticity, which we estimate in Table 9 in the main text:

$$\pi\bar{p}^F \frac{\beta_F^{IV}}{\pi\bar{p}^F\beta^{IV} - \bar{p}\beta_F^{IV}} + (1-\pi)\bar{p}^S \frac{\beta_F^{IV}}{\pi\bar{p}^F\beta^{IV} - \bar{p}\beta_F^{IV}} = \bar{p}\frac{\beta_F^{IV}}{\pi\bar{p}^F\beta^{IV} - \bar{p}\beta_F^{IV}} \tag{B.7}$$

which collapses to the elasticity from the baseline framework: $\frac{\beta_F^{IV}}{\pi\beta^{IV} - \beta_F^{IV}}$ if $\bar{p}^F = \bar{p}^S = \bar{p}$.

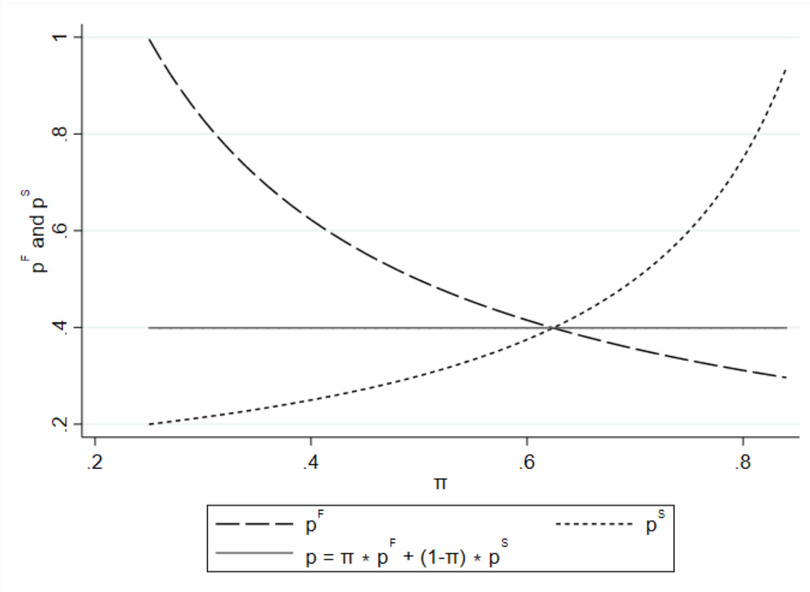
Recall from above that we in the baseline framework with an invariant $\bar{p}$ calculate the fraction π as $\pi\bar{p}^F/\bar{p}$. Inserting this into Equation B.3 from the main text, we get:

$$\frac{\beta_F^{IV}}{\pi\frac{\bar{p}^F}{\bar{p}}\beta^{IV} - \beta_F^{IV}} = \bar{p}\frac{\beta_F^{IV}}{\pi\bar{p}^F\beta^{IV} - \bar{p}\beta_F^{IV}} \tag{B.8}$$

which is exatly the expression from Equation B.7 above. To illustrate this, Figure B.1a shows values of clearance rates $\bar{p}^F$, and $\bar{p}^S$ across values of π and Figure B.1b shows the elasiticities for fast and slow solved crime, ϵ^F, and ϵ^S, across values of π. The figure shows that the weighted average between the fast and slow crime elasticities in Equation B.7 equals the elasticity we report in Table 9. Hence, the results reported in the paper are robust to different clearance rates across fast and slow solved crime.

Going back to our initial example, if fast solved crimes are "low hanging fruits" committed by less skilled criminals and slow solved crimes are committed by more skilled criminals this suggests that the clearance rate for potentially fast solved crimes is larger than the clearance rate for potentially slow solved crimes ($p^F > p^S$). Figure B.1a shows that this implies that the underlying fraction of potentially fast solved crime, π, is smaller than suggested in the main text (if the fast solved crimes we actually link to offenders constitute a larger fraction of total potentially fast solved crimes, then π has to be smaller). Figure B.1b shows that the corresponding elasticity for fast solved crime with respect to the detection probability is thus larger whereas for slow solved crime it is smaller (as the actual response we observe for fast solved crime is now relatively larger because the fraction of fast solved crime is lower).

(a) Detection probability



(b) Elasticity of crime with respect to detection probability

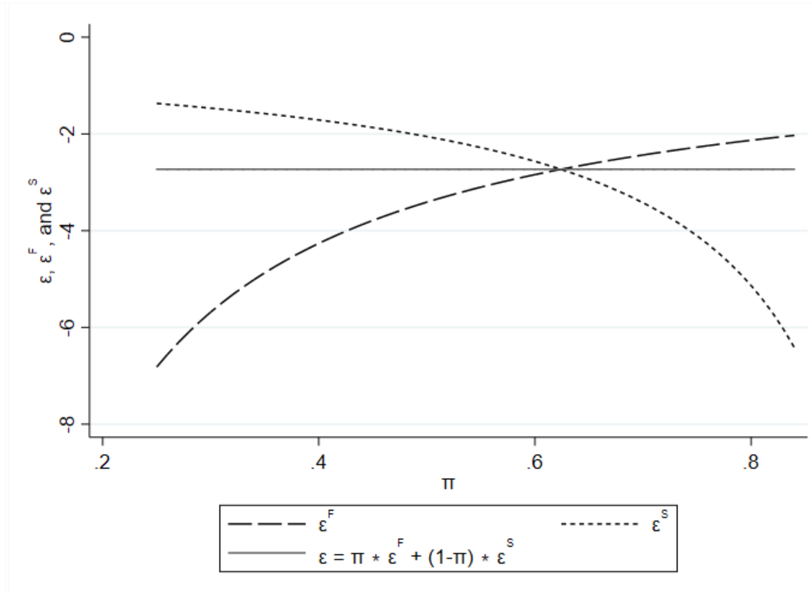


Figure B.1: Consequence of heterogeneous detection probability across fast and slow solved crime across the fraction of potentially fast solved crime π

Note: Figure shows simulation results using the estimates from Table 9. The figure illustrates how hetergeneous detection probabilities across the time it takes to solve a crime would affect our results under the assumption of homogeneous deterrence effects (i.e. the only variation is in the detection probability). Figure A shows detection probabilities across share of crimes that are solved “fast” and “slow”; π. With hetergeneous detection probabilities, the overall detection probability remains unchanged, as it is a weighted average between the different detection probabilities. Figure B shows the corresponding elasticities of crime with respect to the detection probability. Again, the overall estimate is unchanged, as it is weighted average across π. However, the underlying elasticities change such that if we overestimate the share of fast solved crime (low π) then the elasticity of fast solved crime is underestimated and vice versa.

B.3 Heterogenous deterrence effects

In our baseline framework we identify the deterrence effect Δ from fast solved crimes, and use this together with the results for slow solved crimes to isolate the detection effect δ and thus also the elasticity of crime with respect to the detection probability ϵ. We now consider the case where there is not a uniform Δ for the two types of crime, but instead different deterrence effects for fast and slow solved crime Δ^F and Δ^S, respectively.

This complicates things to a larger degree than in the previous subsection. Different deterrence effects can arise for many different reasons as, for example, unobservable heterogeneity or nonlinearity. Hence, there is almost no limit to the possible deviations from our baseline framework. To make progress from this observation and study the consequences of different deterrence effects within our framework, we simply assume that the difference between the two deterrence effects are a scalar $\Delta^S - \Delta^F = d$.

We show below that this not only results in different elasticities of crime with respect to the detection probability for fast and slow solved crimes, it also changes the average estimate; what we report in Table 9 is biased. This bias will, however, be relatively small. If the two deterrence effects differ by 20%, the average elasticity will be biased by approxiately 10% (i.e. be either -2.9 or -2.4 instead of -2.7, depending on the direction of the difference).

Focussing first on fast solved crime, we will still identify the deterrence effect:

$$E[\Delta^F] = \frac{\beta_F^{IV}}{\pi\bar{p}} \tag{B.9}$$

However, we cannot identify the corresponding for slow solved crime. Instead, we now consider the consequence of different degrees of heterogeneity between Δ^F and Δ^S.

We can express Equation B.3 from the baseline framework as:

$$\beta_S^{IV} = (1-\pi)\bar{p}\Delta^S + \gamma DNAy_1 \tag{B.10}$$

As we here consider heterogeneity in the deterrence effect only, the detection effect, δ, will still be given by the last term $\gamma DNAy_1^S$. Furthermore, by inserting the difference between the deterrence effects for fast and slow solved crime, we get:

$$
\begin{aligned}
\beta_S^{IV} = (1-\pi)\bar{p}(\Delta^F + d) + \gamma DNAy_1 \implies& \\
E[\delta] &= \beta_S^{IV} - (1-\pi)\bar{p}(\Delta^F + d) \\
&= \beta_S^{IV} - (1-\pi)\bar{p}(\frac{\beta_F^{IV}}{\pi\bar{p}} + d) \\
&= \beta_S^{IV} - \frac{1-\pi}{\pi}\beta_F^{IV} - (1-\pi)\bar{p}d
\end{aligned}
\tag{B.11}
$$

Hence, if there are heterogeneous deterrence effects, our estimated detection effect will be biased by $-(1-\pi)\bar{p}d$. If the deterrence effect for fast solved crime is numerically larger than for slow solved crime ($d > 0$), we underestimate the detection effect and vice versa.

To see how this affects our estimated elasticity of crime with respect to the detection probability, we use the baseline relationship from Equation B.3 that $\epsilon = \bar{p}\Delta/\delta$, but expand it to allow for heterogeneous deterrence effects:

$$
\begin{gathered}
\epsilon^F = \bar{p}\frac{\Delta^F}{\delta}, \qquad \epsilon^S = \bar{p}\frac{\Delta^S}{\delta} \\
\Downarrow \\
E(\epsilon^F) = \bar{p}\frac{\beta_F^{IV}}{\pi\bar{p}\beta^{IV} - \beta_F^{IV} - (1-\pi)\bar{p}d} \qquad E(\epsilon^S) = E(\epsilon^F) + \frac{d}{\pi\bar{p}\beta^{IV} - \beta_F^{IV} - (1-\pi)\bar{p}d}
\end{gathered}
\tag{B.12}
$$

Figure B.2 shows the resulting elasticities along with the average elasticity across different levels of heterogeneity d.

The figure shows that heterogeneous deterrence effects would result in elasticities that differ subtantially from each other. There is an inverse relationship between the two elasticities across the heterogeneity d. The reason is that a higher d implies a lower deterrence effect for slow solved crime, and thereby also a lower detection effect. This decrease makes the elasticity for fast solved crime increase (because the numerator decreases), while for slow

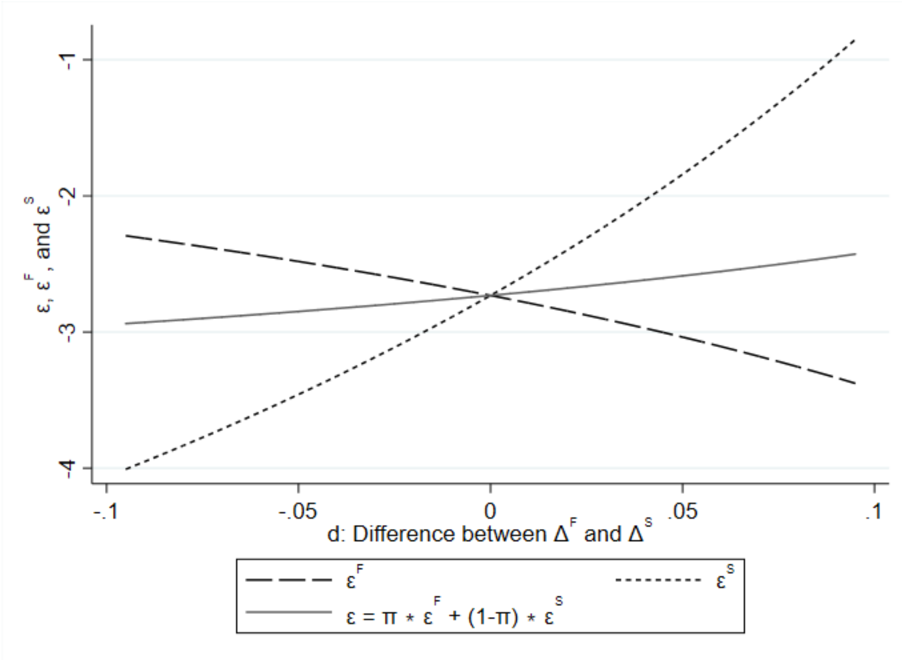


Figure B.2: Elasticity of crime with respect to detection probability in the case of heterogeneous deterrence effects between fast and slow solved crimes
Note: Figure shows simulation results using the estimates from Table 9. The figure shows how heterogeneous deterrence effects across the time it takes to solve a crime would affect our estimated elasticity of crime with respect to the detection probability. The figure plots the resulting elasticities for all crime, and fast and slow solved crime across d, a scalar difference between the two deterrence effects.

solved crime the deterrence effect will decrease at a faster rate than the detection effect (by d and $(1-\pi)\bar{p}d < d$, respectively), thereby reducing the elasticity.

Yet, the figure also shows that the overall impact on the average elasticity of crime with respect to the detection probability is small. If there is a heterogeneity of ± 0.1 in deterrence effects (corresponding to $\pm 20\%$), then the average elasticity would only vary between -2.9 and -2.4, which corresponds to 10% relative to our main estimate of -2.7 from Table 9.

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