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School to Jail Transition – Early Warnings from the Primary School

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ABSTRACT

This study investigates the predictors of incarceration among a cohort of Hungarian primary school students aged 14-15, followed until they are 23-24 years old. We analyze how school quality (including mean test performance and peer characteristics), exclusionary practices, and school/student non-compliance affect the likelihood of incarceration, time spent in prison, and recidivism. Employing linear (OLS) and non-linear (logit, Poisson) models, as well as clustering methods to assess career-path heterogeneity, we identify several key school-level variables as strong indicators of future legal conflicts. The sample comprises 50% of all eighth-graders who were obliged to take a basic competencies test in 2008, with about 1% incarcerated at least once over the next nine years. The predicted probability of incarceration is 0.5% for boys in low-status, well-performing schools, but it increases to 1.0% in low-status, poorly performing schools (at the mean/baseline of other regressors). Absence on the test day raises the risk to 2.8%, and in schools with high grade repetition rates and insufficient support services, the likelihood rises to 8.1%. Although these factors may not directly cause delinquency (some being arguably endogenous), they highlight symptoms associated with a higher risk of criminal behavior, providing valuable insights for targeted interventions by parents and school authorities.

JEL codes: K42, I21

Keywords: incarceration, school quality, exclusionary practices, non-compliance

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Az iskoláktól a börtönig – figyelmeztető jelek általános iskolában

KÖLLŐ JÁNOS – BOZA ISTVÁN

ÖSSZEFOGLALÓ

Ez a tanulmány a börtönbe kerülés előrejelző tényezőit vizsgálja egy 14-15 éves magyar általános iskolás kohorsz körében, amelyet 23-24 éves korukig követünk. Azt vizsgáljuk, hogy az iskola minősége (beleértve az átlagos tesztteljesítményt és a kortársak jellemzőit), a kirekesztő gyakorlatok és az iskola/diák nem szabálykövető magatartása hogyan befolyásolja a börtönbe kerülés valószínűségét, a börtönben töltött időt és a visszaesést. Lineáris (OLS) és nem lineáris (logit, Poisson) modellek, valamint a karrierút heterogenitásának értékelésére szolgáló klaszterezési módszerek alkalmazásával több kulcsfontosságú iskolai szintű változót azonosítunk, amelyek a jövőbeli börtönbe kerülés erős indikátorai. A minta a 2008-ban kompetenciamérésen résztvevő (vagy arról éppen hiányzó) nyolcadikosok 50%-át foglalja magában, akiknek körülbelül 1%-a a következő kilenc év során legalább egyszer börtönbe került. A bebörtönzés várható valószínűsége 0,5% az alacsony státuszú, jól teljesítő iskolákban tanuló fiúk esetében, de 1,0%-ra nő az alacsony státuszú, rosszul teljesítő iskolákban (más magyarázó változók átlagánál, avagy zérus értékénél). A vizsganapon való hiányzás 2,8%-ra emeli a kockázatot, és azokban az iskolákban, ahol magas az osztályismétlési arány és a támogató szolgáltatások elégtelenek, a valószínűség 8,1%-ra emelkedik. Bár ezek a tényezők nem feltétlenül okozzák közvetlenül a bűnözést (némelyikük vitathatóan endogén), rávilágítanak a bűnözői magatartás magasabb kockázatával összefüggő tünetekre, és értékes ismereteket nyújtanak a szülők és az iskolai hatóságok célzott beavatkozásaihoz.

JEL: K42, I21
Kulcsszavak: börtönbe kerülés, iskolaminőség, kirekesztő gyakorlatok, szabálykövetés

School to Jail Transition – Early Warnings from the Primary School*

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Abstract. This study investigates the predictors of incarceration among a cohort of Hungarian primary school students aged 14-15, followed until they are 23-24 years old. We analyze how school quality (including mean test performance and peer characteristics), exclusionary practices, and school/student non-compliance affect the likelihood of incarceration, time spent in prison, and recidivism. Employing linear (OLS) and non-linear (logit, Poisson) models, as well as clustering methods to assess career-path heterogeneity, we identify several key school-level variables as strong indicators of future legal conflicts. The sample comprises 50% of all eighth-graders who were obliged to take a basic competencies test in 2008, with about 1% incarcerated at least once over the next nine years. The predicted probability of incarceration is 0.5% for boys in low-status, well-performing schools, but it increases to 1.0% in low-status, poorly performing schools (at the mean of other regressors). Absence on the test day raises the risk to 2.8%, and in schools with high grade repetition rates and insufficient support services, the likelihood rises to 8.1%. Although these factors may not directly cause delinquency (some being arguably endogenous), they highlight symptoms associated with a higher risk of criminal behavior, providing valuable insights for targeted interventions by parents and school authorities.

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1 Introduction

To explore the roots of criminal behavior, one must look beyond the individual and consider the environments that shape a person's trajectory. This study delves into the critical role of schools in either steering students toward integration into society or, conversely, setting them on a path toward incarceration. We follow a fifty-percent random sample of 14-15-year-old Hungarian primary school students (eight-graders) between May 2008 and December 2017. Slightly more than one percent of these students were incarcerated at least once during this period. We study empirically how school quality, exclusionary practices, and non-compliance with the rules for students and schools predict this event.

Schools differ in tuition quality (measured here by mean reading test performance) and students' social backgrounds. Both attributes affect students' chance to integrate into the society of 'ordinary people'. Teachers develop their skills and try to pass on mainstream social norms more or less successfully, while parents and peers may help or hinder them. These forces interact due to a strong correlation between schools' test performance and their students' parental background, on the one hand, and the concentration of good teachers in schools attended by high-status pupils.

Schools also differ in how they deal with hard-to-teach students. Several forms of exclusion—like regular recourse to class repetition, special classes for low-achievers, and the lack of tutoring outside lessons—may drive pupils toward a track that leads to the penitentiary system.

Last but not least, we can hypothesize that students and families who disobey the rules now (do not show up at compulsory tests or fail to provide information about their social backgrounds) are more likely to breach the law in the future, other things equal. Likewise, schools that do not respect their obligation to participate in mandatory surveys conducted by the educational authority are less likely to propagate the ideal of the law-abiding citizen.

We do not think any of the abovementioned factors directly and strongly impact delinquency. We only assume that they complement a complex set of personality traits, social impulses, economic forces, persuasive fellowships, and temptations that drive some young people to commit crimes.

After a brief overview of the literature and discussing the Hungarian specifics, we introduce the data and provide descriptive statistics on the sampled students' proceeding in education, the labor market, and incarceration. A lengthier section deals with measurement and estimation issues. We then estimate linear and non-linear equations to study how our key variables predict the probability of imprisonment, the time spent in prison, and the number of prison spells from 2008 to 2017. We also estimate the models on the school level. To benefit from the panel structure of the data, we create sequences of mutually exclusive states (participation in education, incarceration, and three indicators of labor market status) and cluster the status sequences into three types, pulling together the most similar histories by minimizing within-cluster variation. We then re-estimate the incarceration equations group by group.

Our analysis has to cope with limitations stemming from the very nature of the phenomenon under scrutiny. First, incarceration is a rare event that has implications for the choice of models. The low absolute number of incarcerations (730 cases in 124 months) rules out an event history approach. Even in a cross-section investigation, we must choose models suited for rare-event analysis and resistant to quasi-separation. Second, factors raising the probability of imprisonment also increase the likelihood of non-cooperation with the school. Our follow-up starts with a nationwide, all-encompassing, mandatory competence test supplemented with a rich background questionnaire on family composition and neighborhood characteristics – a promising toolbox for analyzing who becomes a prisoner. However, only 68 percent of future prisoners took the competence tests, and 35 percent filled out the background questionnaire; therefore, we know little about their school performance and even less about their social backgrounds.[1]

These deficiencies do not exclude a valuable contribution to the literature. We have reliable information on schools' mean test performance, the composition of their students by family background, how they deal with challenging students, and how they comply with the rules prescribed by the education authority. The data on schools are abundant for a study of how these characteristics contribute to students' later involvement in crime. Furthermore, while our knowledge of the initial state of students' careers is limited, we have detailed information on their post-2008 school attendance, employment relationships, employers, job characteristics, earnings, unemployment, and transfers.

The problems of non-random selection, endogeneity, and 'bad controls' obviously arise in a (basically) cross-section examination in the absence of exogenous shocks. First, what we interpret as the school's contribution to a student's incarceration may arise from a correlation between school quality/school practices and unobserved family and neighborhood characteristics predisposing to crime. Second, non-compliance with the rules now and incarceration in the future can be by-products of an environment in conflict with the law and the ruling behavioral patterns. We discuss these confounding factors in a methodological section and take action to mitigate their influence.

Our main findings are the following. i) Unsurprisingly, the graduates of schools with below-average test performance and above-average share of students from low-status families are more likely to be imprisoned. ii) Less evidently, the effect of test performance is stronger if the fraction of low-status children is high, and conversely, family background has a more robust effect in the zone of bad schools. iii) The impact of school quality on incarceration is most substantial in the sub-sample, where the status sequences hint at serious offenses. (iv) School-reported psychological and behavioral deficiencies and the failures of student-school and family-school cooperation (absence on the day of the tests, failure to provide data on parents and the neighborhood) are powerful predictors of a criminal record. Schools not reporting data to the educational authority have more incarcerated students. (v) Exclusionary practices in the school, like a higher rate of grade repetition, the separation of low-achievers, and the lack of tutoring outside classes, are associated with an increased probability of incarceration among their students.

2 Literature

Education and Crime

Theory implies that education plays a crucial role in future crime outcomes through multiple aspects. First, higher education leads to better labor market outcomes, decreasing the payoffs from committing crime. Even if better education decreases incarceration probabilities or the expected length of incarceration, the expected marginal returns from education to labor outcomes are larger than those from criminal activity. Other channels include increased risk aversion and patience, which lead to a lower expected crime rate among more educated groups (Lochner, 2020).

[1] Fortunately, we have information on students classified as having 'multiple social disadvantages' (MSD). In our time window, a student could be classified by an authorized notary as MSD if at least two of the following three conditions held: i) The family head had at most primary education background, (ii) The family head was non-employed, (iii) The child lived in a sub-standard dwelling. The MSD variable is available for more than 99 percent of the sample and provides a second-best measure of low social standing.

Estimating a causal effect of educational attainment is confounded by non-cognitive skills or features. Present-biased or risk-taker individuals tend to choose lower levels of education. Hence, most studies that estimate a causal effect of education on crime rely on natural or quasi-experimental settings, such as changes to compulsory schooling age or dropout policy (Bell et al., 2022). For a summary of earlier studies, see Lochner (2020). The consensus is that more education indeed decreases future incarceration rates and crime activity. Policy programs targeting the youngest generations are particularly effective (Eriksson, 2020; Heckman et al., 2010).

There is, however, a smaller literature focusing on the intensive margin of education, i.e., not directly on the level or length of education but on its quality. One branch identifies school quality from student preferences and uses random admittance around a threshold as a source of variation. Huttunen et al. (2023) study the impact of access to secondary education on crime rates among young men in Finland. Despite finding that gaining admission to (any) secondary school significantly reduces the likelihood of committing crimes, no effect exists on the intensive margin. Getting into general (instead of vocational) schools or more selective schools does not decrease crime rates significantly. However, Deming (2011) examines the long-term impacts of attending a first-choice middle or high school on criminal behavior. They find that students who attend their preferred school are significantly less likely to be arrested or incarcerated as adults. The effects are especially strong among high-risk youth, indicating that school quality and peer influences are crucial in reducing criminal activities. Similarly, Cullen et al. (2006) find that winning a school choice lottery in the Chicago Public Schools leads not only to attendance at higher-quality high schools but also to improvements in nontraditional outcomes, such as reduced self-reported disciplinary incidents and lower arrest rates.

Most recently, Baron et al. (2024) investigate whether increasing public school funding can serve as an effective long-term crime-prevention strategy in the U.S. Utilizing quasi-experimental variation in public school funding from two natural experiments in Michigan, they find that students who received additional funding during elementary school were significantly less likely to be arrested as adults. Earlier, using a survey design, Johnson and Jackson (2019) investigate the combined effects of Head Start and K-12 educational spending on long-term outcomes for poor children. They find that increased spending in these areas boosts educational attainment and earnings while reducing poverty and incarceration rates. Cano-Urbina and Lochner (2019) aim to directly link school quality measures to criminal outcomes and show mixed results. Their research indicates that higher average state schooling levels decrease arrest rates for violent and property crimes but not for white-collar crimes. However, the authors find small and mixed (inconsistent) direct effects of school quality on crime.

Using external variation of a different kind, Weiner et al. (2009) find that court-ordered school desegregation significantly reduces homicide victimization and arrests among black youth by around 25 percent, with positive spillover effects to other groups. Their study attributes these reductions in part to increased schooling attainment and suggests that such desegregation orders lowered the national homicide rate for black teens and young adults by approximately 13 percent. This effect may account for about a quarter of the convergence in black-white homicide rates from 1970 to 1980.

Mechanisms

An important finding of Baron et al. (2024) is that lower incarceration rates are not purely driven by better academic results or educational attainment, as these can explain only one-fifth of the effect on crime rates. At least twice as important are the effects on absenteeism. The authors argue that, besides academic merits, better funding and, hence, better working conditions in schools can affect crime through non-cognitive skills as well. These results are consistent with the findings of Rose et al. (2022), who investigate the impact of teacher quality on students' future interactions with the criminal justice system (CJC). They find that higher teacher quality is associated with a significant reduction in students' future arrests, with a standard deviation of teacher effects leading to a 2.7 percentage point decrease in arrests. Teachers focusing on reducing suspensions and improving attendance also substantially lower future arrests, emphasizing the importance of fostering non-cognitive skills.

The role of teaching or school management practices is also highlighted by Wolf and Kupchik (2017), who investigate the long-term effects of school suspensions on students' future criminal behavior. They find that students who are suspended are more likely to experience criminal victimization, involvement, and incarceration as adults. Pesta (2018) examines the differential impact of exclusionary school discipline on various ethno-racial groups. They find that such disciplinary practices disproportionately affect minorities and lead to adverse life outcomes, including higher dropout rates, increased delinquency, and criminal offending. The study highlights significant variations in the impact of school exclusion across different ethno-racial groups, pointing to the need for more equitable disciplinary practices. These findings suggest that exclusionary practices have adverse and lasting impacts on students.[2]

Besides the direct effects on cognitive and non-cognitive skills, education can also influence criminal outcomes through peer effects, as education often affects whom people will interact with as adults, whether in family, work, or further education (Lochner, 2020). Cano-Urbina and Lochner (2019) suggest that the impact of education on female crime is primarily associated with changes in marital opportunities and family formation and not primarily led by better employment outcomes for women themselves. It is important to note that such peer effects can confound the direct effects of education on criminal behavior.

Finally, mental health may also play a role. Butikofer et al. (2020) find that attending more selective high schools in Norway decreases the probability of experiencing psychological issues. The positive impact is more pronounced with significant changes in student-teacher ratios and teacher characteristics, indicating that teacher quality is crucial. However, incarceration itself can have an unintended effect on mental health. For instance, Løken et al. (2023) find that incarceration leads to a decrease in mental health disorders among both defendants and their spouses, as evidenced by fewer mental-health-related visits to healthcare professionals.

A strand of research directly relevant to our study is nicknamed the 'school to prison pipeline literature' (SPP) (Rocque and Paternoster, 2011; Skiba et al., 2014; Merlo and Wolpin, 2015; Rocque and Snellings, 2018 among others). SPP deals with the use of law enforcement, rather than discipline and aid, to address behavioral problems in schools. These practices gained momentum after the introduction of zero tolerance vis-à-vis breaches of discipline (including minor ones) in most US schools. Zero tolerance resulted in a growing number of suspensions and expulsions, forwarding within-school problems to the police, more drop-outs, and a spectacular rise in the number of arrests, convictions, and incarceration, mostly among black youth. While formal zero-tolerance policies did not exist in Hungary in the time window of our study (school guards employed by the police only appeared on the scene in

[2] Perry and Morris (2014) show that higher levels of exclusionary discipline in schools negatively impact even the academic performance of students who are not suspended. This adverse effect is evident even in schools with low levels of violence, suggesting that excessively punitive policies are detrimental to the entire student body. This may partly explain the effects on criminal outcomes as well.

2020), responding to affray and arrears with exclusion (Nagy 2009) can be a familiar feature for US readers.

3 Local specifics

This section briefly discusses some specifics of education in Hungary, the penitentiary system, and the labor market that the general reader might find helpful.

Education

The Hungarian educational system comprises eight-grade primary schools, three or four-grade vocational training schools, typically four-grade secondary schools, and colleges. Exceptions exist: some secondary schools run classes from the 5th (or 7th) to the 12th grade, and movement from primary to secondary schools may occur after completing grade 4 or 6 of the primary school. (For details, see Eurydice 2024). A public school belongs to a school district but has the right to admit applicants from other districts after admitting all applicants from its catchment area. Children are free to apply to schools outside their district. Private and church-run schools do not belong to any catchment area and are free to admit applicants without any limitation. The freedom of choice guaranteed for both sides results in an exceptionally powerful relationship between schools' social background and academic performance (Jenkins et al., 2008; Kertesi and Kézdi, 2012; Schleicher, 2018; Holmlund and Öckert, 2021; Hajdu et al., 2021).

Incarceration and its aftermaths

We identify prisoners based on social security contributions transferred by the central budget to the Health Insurance Fund during a person's detention. We know the start and end dates of incarceration but have no information on the type of detention. Prison statistics suggest that about 20 percent of the incarcerated are in pre-trial detention (typically spent in prison). Others serve their sentences in three kinds of facilities of different stringency. This paper speaks of prisoners (incarcerated, convicts, inmates) who spent time behind bars between 2008 and 2017.

Hungary's incarceration rate ranged between 0.16 and 0.19 percent in our observation period – a level deep below those reported for the US (0.6-0.7) and the post-Soviet states (0.3-0.4) but higher than the EU average (Walmsley, 2018). More than 30 percent of the first-time entrants to the penitentiary system are younger than 25. While incarceration before age 18 is infrequent, those between 18 and 25 have a 2.2 times higher probability of imprisonment than their older counterparts.[3] The fraction of those incarcerated at least once, who possibly wear a stigma and face difficulties in reintegration, is much higher than that.[4]

Even a short prison spell has long-lasting consequences. Civil and public servant positions can only be filled after presenting clean records. In practice, all public sector employers require a clean sheet for all jobs, and about 25-40 percent of private companies do so, according to a survey by Csáki and Mészáros

[3] Authors' calculation using the Admin3 (2024) panel of 2003-2017.

[4] A generation life table calculation suggested that about 6.7 percent of the male population would be incarcerated at least once by age 64 if the age-specific first-incarceration rates remained at their 2009-2011 levels (Köllő et al., 2024). This slightly upward-biased estimate is close to the 6.2 percent reported by Skardhamar (2014) for Norway and markedly lower than the 11.3 percent estimate by Bonczar (2003) for the US. The Köllő et al. paper found that 3.7 percent of the 15–49-year-old males with no secondary school attainment had prison experience in nine years preceding the calculation. Among the registered unemployed, 7.2 percent were incarcerated at least once, with the estimate for the unskilled unemployed amounting to 10.1 percent. Győri (2013) reported that 6.7 percent of homeless people in the countryside and 3.7 percent in Budapest got to the street after being released from prison.

(2011). The time until the records are clean depends on the sentence's duration: it takes 3, 5, 8, and 10 years after penalties shorter than one year, 1-5 years, 5-10 years, and more than ten years, respectively. In these periods, ex-inmates are also excluded from managerial positions in micro-firms and sole proprietorships. Released prisoners can apply to a court for expungement, but their requests are rarely approved.

Public Works (PW) and registered casual work (CW)

PW and CW play a vital role in the employment of Hungarian ex-convicts. PW is a large-scale program for the long-term unemployed, typically providing simple jobs in street cleaning, road and park maintenance, forestry, and (less frequently) social services. Registered unemployed can be called to do public works on short notice, at any time, and for any duration. Declining a call may imply exclusion from unemployment assistance for three years. In our time window, the remuneration was equal to the minimum wage until 2011 and about 25 percent lower later. At its peak in 2016, PW employed 6 percent of all workers and 22 percent of unskilled workers – extremely high ratios in international comparison.[5] CW allows lower taxes and simplified administration for a limited period, mostly in agriculture, tourism, and the film industry.

Note that employment policy programs targeting released prisoners were missing, but those available for employers hiring long-term unemployed could reach some ex-convicts. Legal institutions and procedural rules aimed at reducing discrimination at hiring and decreasing the risks of employing former inmates (like Ban-the-Box regulations, business crime insurance, and legal responsibility for negligent hiring) did not exist in our observation period.[6]

4. Samples and data

Our explanatory variables were drawn from three educational registers and a large linked student/school and employee/employer panel called Admin3.

Table 1: Status in the National Assessment of Basic Competences (NABC), May 2008

NABC status	Incarcerated No	Incarcerated Yes	Percent incarc-erated	Availability of data on incarcerated students': test scores	family backg.	school ID[a]	SEN, MSD[b]	labor career[c]
Test and family background	67.0	34.8	0.6	+	+	+	+	+
Test, no family background	23.7	28.1	1.2	+	-	+	+	+
Absent	5.3	23.9	4.5	-	-	+	+	+
SEN, tested[d]	2.8	5.3	2.0	-	-	+	+	+
SEN, not tested	1.2	7.9	6.4	-	-	+	+	+
Total	100.0	100.0	1.0					
Number of observations	50,312	531		362	185	531	499	531

Sources: Admin3 NABC, NABC, NABC PILOT

a) Person, school, and firm IDs are anonymized in Admin 3

b) SEN: special education needs. MSD: multiple social disadvantages, a category based on parents' education, employment, and neighborhood characteristics. Students so classified were entitled to special financial support in our observation period.
The SEN and MSD variables have been merged to the Admin3 dataset via probabilistic matching, successful in 94 percent of the cases.

c) Labor market status, employer, dates of entry and exit, job grade, earnings, and similar data on half of the coworkers

d) Schools can decide to test SEN students to help teachers work with them. Their results are not reported to the Office of Education.

[5] Authors' calculations using the Labor Force Survey. Unskilled stands for workers with a primary school background.

[6] In 2018, firms were banned from requiring clean criminal records without thorough justification. Note that Ban-the-Box regulations have ambiguous effects on discrimination (Doleac and Hansen, 2020; Rose, 2019; Jackson and Zhao, 2017; Agan and Starr, 2018).

(i) *National Assessment of Basic Competences* (NABC). Since 2008, the NABC has covered all grade 6, 8, and 10 students who take reading and mathematics tests. The tests have been elaborated in the spirit of PISA; they aim to measure cognitive skills rather than book knowledge. The survey involves a family background questionnaire to be filled out by the students and their parents. For a detailed description of NABC, see Balázsi (2006). We rely on a 50 percent random sample from the 2008 NABC (the first wave integrated into the Admin3 panel), which covered 50,843 students, of whom 531 were incarcerated at least once from 2008 to 2017.[7] As shown in Table 1, only 63 percent of the future inmates took the NABC tests, and 35 percent filled in the background questionnaire – this compares to 90 percent and 67 percent in the general student population, respectively. Almost a quarter of the future prisoners were absent on the day of the tests (compared to only five percent of the non-incarcerated), and they were also heavily over-represented among students exempted from the tests for reasons of behavioral or mental disorders or special education needs (SEN). As discussed in Csépe (2009), hard-to-handle pupils are often classified as SEN without proper medical justification, and this also relates to those exempted from the tests for behavioral deficiencies. The incarceration rates in the non-responding groups were 2-6 times higher than the average.

ii) *NABC Pilot Stage.* A NABC wave is preceded by a pilot survey in which schools provide data on their students at the individual level. This is where we know students' classification as MSD and their mathematics grades in the semester preceding the survey. We could merge the pilot survey data to the NABC using hash-coded student IDs. Non-participation in the pilot stage is rare and evenly distributed across types of schools.

iii) *NABC Establishment Survey*. Schools are obliged to provide information about their establishments (premises). This survey provides information on grade repetition rates, separate classes for low-achievers, tutoring outside classes, and the share of Roma students. The survey can be merged with our data using hash-coded school IDs. The establishment survey is missing in 13 percent of the schools teaching 13 percent of the students. The non-responding schools are not randomly selected: 9.5 percent of the public schools, 38.7 percent of the church-run schools, and 29.8 percent of the private schools failed to send data. The differences by type of school are even sharper: 4.9 percent of the primary and 87.8 percent of the secondary schools failed to report data on their establishments.

iv) *Admin3*. Data on participation in education and labor market careers have been drawn from a linked employer-employee panel, which follows 50 percent of Hungary's resident population and their employers monthly from January 2003 to December 2017. The data are detailed in KRTK Databank (2024) and Sebők (2019). We merged our sample to Admin3 using hash-coded social security numbers.

Table 2 gives an overview of the samples used in the paper. We provide descriptive statistics on the *entire sample*, estimate incarceration equations without variables on exclusionary practices (*broad estimation sample*), and exploit complete information on students and schools relying on a smaller sample (*narrow estimation sample*). The means and standard deviations of the variables in the broad and narrow estimation samples are provided in Appendix Table A1.

[7] The Hungarian regulations (Law 2007. CI) allowed a maximum of 50 percent sampling quota for academic research working with linked administrative panels.

Table 2: Samples used for descriptive statistics and estimation

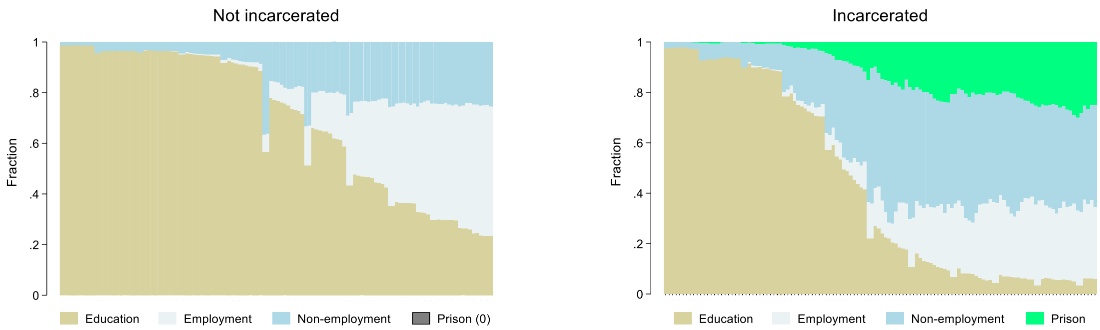
Number of observations:	Incarcerated No	Incarcerated Yes	Total	Incarceration rate (percent)
Entire sample: includes all students. Data on participation in education, labor market careers, and incarceration are available—no data on multiple social disadvantages, mathematics grades, and school-level exclusionary practices.				
Cases included	50,312	531	50,843	1.04
Broad estimation sample: This includes the students of schools that responded to the pilot survey. Data on multiple social disadvantages and mathematics grades are available; those on exclusionary practices are not.				
Cases included	50,014	499	50,513	0.99
Cases excluded	298	32	330	9.88
Narrow estimation sample: includes the students of schools that responded to the pilot and establishment surveys. Data on school-level exclusionary practices are available.				
Cases included	43,703	469	44,172	1.06
Cases excluded	6,609	62	6.671	0.92

The incarceration rate in subsamples distinguished in the table is known. The rates are similar across subsamples except for one: the students of schools not responding to the pilot survey had a nearly 10 percent incarceration rate, ten times the average. These schools are evenly distributed across controlling authority (state, church, private) and type (primary or secondary). However, nearly all their students were either absent on the test day (61 percent, obliged to participate) or exempted (38 percent).

5 Descriptive statistics

Fig. 1 depicts the career paths of incarcerated and non-incarcerated students between May 2008 and December 2017. Those who ended up in jail left the educational system earlier and were predominantly non-employed after school. In the second half of the observation period, the fraction of those in education or employment leveled off at 0.4 in the former group and 0.8 in the latter group. We now present information on each status distinguished in Fig.1.

Figure 1. Education, employment, and incarceration, May 2008-December 2017



Source: Admin3. Horizontal axis: months between May 2008 and December 2017

Incarceration. Table 3 presents selected indicators of those incarcerated at least once between 2008 and 2017. The probability of this event was 1.04 percent. About 30 percent had more than one prison spell by age 23-24. The average duration of prison spells amounted to 18 months, but the median spell was only nine months long. The inmates were, on average, 21 years old at their first incarcerations, suggesting a gap of about three years between exit from education and first imprisonment.

Table 3. Incarcerations – Selected indicators, 2008-2017

Probability of incarceration (percent, all students = 100)	1.04
Number of prison spells (percent, all prisoners = 100)	
- One	71.9
- Two	21.3
- Three or more	6.8
Duration of the prison spells (months)	
- Median	9
- Mean	18.2
- Standard deviation	20.6
Median age at the first incarceration (years)	21
Incarcerated persons	531
Incarcerated persons' person-months	50,843

Sample: 8th-grade students incarcerated between May 2008 and December 2017

Table 4: Education and labor market career - percent, exceptions indicated

	Not incarcerated	Incarcerated
School attendance before and after the school leaving age (SLA)[a]		
12 months before the SLA	96.8	94.1
At the SLA	95.3	86.3
12 months after the SLA	77.6	33.7
Educational attainment in December 2017 (at age 23-24)		
Incomplete primary	0.4	4.6
Primary	13.4	72.7
Vocational	13.1	14.9
Secondary	58.5	6.8
Higher	14.6	0.0
Total	100.00	100.00
Employment in 2008-2017		
Time in employment	22.8	17.8
Time in employment if out of education	51.8	24.4
Time in employment if out of education and prison	51.8	29.2
Employed six months after leaving education	54.2	20.6
Type of employment in 2008-2017		
Employee	81.3	54.4
Self-employed, business partner	3.2	0.6
Registered casual worker	8.5	22.1
Public works participant	7.0	22.0
Total	100.0	100.0
Occupations in 2008-2017		
White collar	23.0	2.8
Trade and service worker	20.7	5.8
Skilled blue collar	14.3	13.8
Assembler, machine operator	16.0	14.5
Elementary	26.1	63.1
Total	100.0	100.0
Wage disadvantage (2008-2017, OLS estimates, log points)		
Controlled for month fixed effects	..	-0.267
Controlled for month fixed effects, type of employment, and occupation	..	-0.113
Duration of the employment spells (months)		
Uncensored spells: tenure at the exit from the employer[c]		
- Mean	5.4	3.0
- Standard deviation	6.9	3.9
Right-censored spells: tenure in December 2017		
- Mean	14.6	7.2
- Standard deviation	13.4	9.3
Observations		
- Persons	50,198	531[b]
- Person-months	1,470,706	12,741
- Number of employment spells	122,182	2,618

Source: Admin3, Sample: Year-2008 8th grade students

a) The school leaving age was 18 years for those in the sample

b) Data on educational attainment are missing in 11 cases

d) Spells in progress on the 15th day of month *t* and completed before the 15th day of month *t*+1 were assumed to have started on the first day of month *t* and ended on the last day of month *t*.

As shown in Table 4, most (92.5 percent) future inmates continued their studies in 2009, and 89 percent remained in school until 2010. A significant drop came the next year when cohort members started to reach age 18, the school-leaving age (SLA) relevant to them. Only one-third participated in education one year after reaching the SLA, as opposed to nearly 80 percent in the non-incarcerated population.

Future inmates typically leave the educational system without acquiring secondary-level qualifications. At the end of our observation period, 77.3 percent had only primary school attainment, and none of them had graduated from higher education

Persons with prison experience spent 29 percent of their time out of school and prison compared to 52 percent in the general population. They were much more likely to work as CW and PW participants and less likely to be employed in standard jobs or as self-employed. Almost two-thirds of them attended an elementary job. They earned less by 0.27 log points overall and 0.11points within occupations and types of the employment relationship. Their jobs were typically short and dissolved in the fourth month on average. (Note that the jobs of the non-incarcerated were also relatively short, as expected with people at the start of their labor market careers).

Schools. The cohort members attended 2,441 schools in May 2008, of which 17.2 percent had at least one 8th-grader incarcerated later. The high fraction of affected units is explained by the low percentage of schools 'sending' more than one student. We do not see particular schools delivering inmates to the penitentiary system on a massive scale. However, the lack of concentration does not imply that schools are randomly selected for the group of deliverers.

Table 5. Schools by the number of 8th-grade students incarcerated later at least once (percent)

None	One	Two	More	Total	Obs.
82.8	13.6	2.8	0.8	100.0	2,441

Source: Admin3. The data relate to the 8-graders of May 2008 followed until December 2017.

6 Measuring school-level indicators

School performance. We measure school performance by the average 8th-grade NABC reading comprehension test scores. (Using the mathematics scores would yield virtually identical results.) The measurement error due to students not taking the tests is not vital since their share falls short of ten percent.

Family background is more difficult to quantify, given a relatively large set of correlated indicators to choose from. We rely on four indicators, measuring the school-level share of students coming from families with (i) no working parent, (ii) no parent with more than primary educational attainment, (iii) at least one parent having tertiary education background, (iv) of Roma ethnicity, as reported by the school, and (v) a 'Roma ethnicity missing' dummy. The factor analysis draws a powerful first principal component with an eigenvalue of 2.4 (see Appendix Table A2).

Table 6. Mean values of the constituent variables in quintiles of students ordered by the family background indicator (variables with high factor loadings in the first principal component)[a]

	Quintiles					Entire
	1	2	3	4	5	sample
Highest-educated parent: Primary	22.3	7.8	3.4	1.4	0.7	7.1
No wage earner in the family	14.4	4.4	1.7	0.9	0.5	4.4
Roma share if observed[b]	44.3	16.8	6.3	3.8	1.5	16.2
Roma share missing	2.2	1.0	2.3	4.5	53.5	12.5
At least one parent is highly educated[c]	4.7	9.3	11.5	21.8	41.8	17.7

Sample: students responding to the NABC background questionnaire in schools responding to the NABC establishment survey. N= 34,051

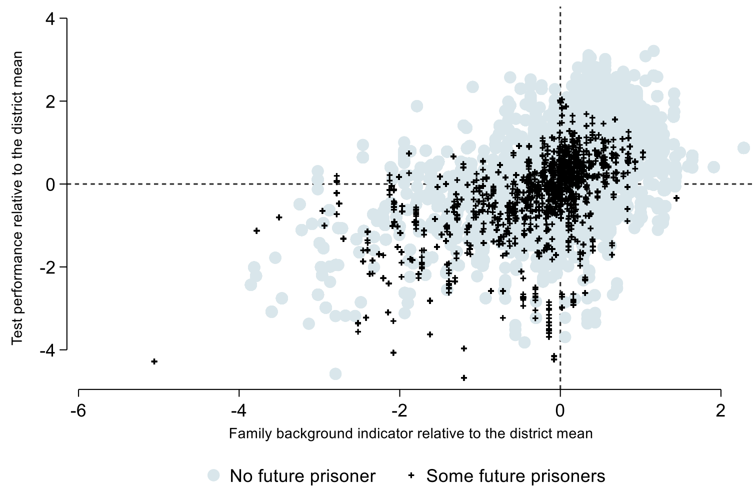
a) The constituent variables are school-level. Calculating the means for student quintiles is tantamount to weighting the schools by their size. b) In the estimations, this variable is set to zero if the 'Roma share missing' variable equals one.

The constituent variables vary widely in quintiles of students ordered by this principal component (Table 6). The shares of unskilled and unemployed parents and the Roma share are about 30 times higher in the first than in the fifth quintile, while the fraction of highly educated parents is lower by about 90 percent. Remarkably, more than half of the elite schools (fifth quintile) were reluctant to answer the question on Roma share, compared to one-digit percentages in other quintiles.

Choosing reference. We normalize the test performance and family background indicators using their district-level means. The district (*járás*) is considered the geographical unit that best approximates the boundaries of the local labor market. On average, the districts have 57,000 inhabitants and are relatively closed, except for the capital and its agglomeration: according to the 2011 census, on average, 85 percent of a district's jobs were held by residents. The districts differ substantially in mean test performance and family background (Appendix Table A3). Since students typically enter these local labor markets, their within-district disadvantages matter more for their careers than their position in the nationwide distribution. For the sake of brevity, we continue to speak about 'test performance' and 'family background,' not forgetting that they stand for within-district indicators.

Dichotomization. Figure 2 depicts how schools are located in the space of test performance and family background. Schools teaching at least one future prisoner are marked with a plus sign.

Figure 2: Schools in the space of test performance and family background



Our models distinguish schools by their attachment to one of the four areas of the chart. At least two arguments support this simple approach. First, using continuous variables, we could not separate the effects of test performance (T) and family background (F) on prison experience (P) – the parameters of an equation P=f(T, F) would be biased by the mutual dependence of T and F. Estimating T=f(F) and treating the residual as a measure of teaching quality would also produce a biased coefficient and residuals.[8] Instrumenting F with a similar indicator relating to the school district (F^*) would be technically feasible but questionable, too, since F^* may affect P through channels other than its impact on F. Second, the continuous T variable is noisy: the school-level test score in year *t* is a poor predictor of the test score in year *t*+1. We examined 24,627 one-year transitions between test score deciles in 2008-2017: apart from the worst and best 1/10 of the schools, the probability of staying in the base-

[8] This is how the Hungarian Office of Education measured school performance in our time window.

period decile amounted to only about 25 percent. By contrast, below-average and above-average positions were stable, with 80 percent of the schools preserving their base-period location.

The distribution of schools teaching future prisoners is biased away from elite schools and toward low socio-economic status combined with poor test performance: 30.4 percent belong to the upper-right section (compared to 46.7 percent overall), and 44.4 percent (compared to 23.4 percent) lie in the lower-left segment.

Two closing remarks apply. First, we discuss the bias from dichotomization in the Methods section. Second, we use an alternative measure of a school's test performance by looking at how its graduates perform at the 10-grade (secondary school) NABC test relative to their new schoolmates. This measure is less exposed to the mutual dependence of family background and test scores than when we use the 8-grade indicators.

Proxies of school-level non-compliance. We observed schools that did not report data to the Office of Education in the pilot stage and/or the establishment survey. Incarceration rates are known for these schools and their students.

School practices. We chose three indicators relevant to our topic: the grade repetition rate, the opening of separate classes for low achievers, and the lack of tutoring outside classes. The data in Appendix Table A4 suggest that school quality and exclusionary practices are weakly correlated.

7 Methods

The general form of the incarceration models we estimate is the following:

[1] $Y_{kij} = f\left(X_i, S_{ij}, Z_{ij}\right), k = 1,2,3$

where *i* stands for individuals and *j* denotes schools. Y_{1ij} is the probability of incarceration at least once, Y_{2ij} is months spent behind bars, and Y_{3ij} is the number of prison spells from 2008 to 2017. The person-specific *X* variables are gender, a dummy for being older than 16 in 2008, an indicator of multiple social disadvantages as defined by the school, SEN status, mathematics grade relative to the class mean in the semester preceding the NABC test, and a measure of crime incidence among the residents of person i-s district.[9] In our benchmark specification, we also include dummies denoting status in the 2008 NABC (did not fill in the background questionnaire, was absent or exempted). The *S* dummies distinguish the four school types introduced in the previous section. The *Z* variables relate to exclusionary practices in person i-s school j.

We estimate the Y_1 equations with a penalized maximum likelihood model proposed by Firth (1993) and applied to Stata under the name *firthlogit* by Coveney (2015). The model is better suited for analyzing rare events and more robust to quasi-separation. The Y_2 equations are estimated with OLS, while we use a Poisson model with robust standard errors for Y_3.

We discuss three problems that could potentially jeopardize the estimates: endogeneity, the bias from dichotomization, and potential bad controls.

[9] The NABC Pilot survey records the mathematics but not the reading grade, which we consider throughout the paper. The crime rate is calculated as the number of residents incarcerated in 2003-2017 divided by the district's mean population.

Endogeneity. The coefficients of Eq. 1 may reflect a correlation between school quality/school practices and unobserved family and neighborhood characteristics predisposing to crime rather than the school's contribution to a student's incarceration. This problem may manifest in different ways:

(i) School performance can be directly affected by the presence of students incarcerated later. (ii) Good-performing and high-status schools could (in principle) reject crime-prone applicants. They are left behind in bad schools but go to jail for reasons other than school quality. (iii) Families can move to better school districts to avoid crime-prone peers. (iv) Many students leave low-status, poor-performing schools after grade 6. One of their motives can be escape from a crime-prone environment. Incarceration among the remaining students can be high for reasons rooted in their home environment. (v) Exclusionary practices may respond to a crime-infected studentry.

While most of the mechanisms leading to reverse causality have some truth to them, the observed and reasonably assumed magnitudes cast doubt on the strength of their effects.

First, the percentage of incarcerated students is sufficiently low not to affect a school's performance substantially. *Second*, rejecting crime-prone applicants is an option for church-run and private schools (attended by 10 percent of the sampled students) but not for public ones – they must admit all applicants from their catchment area. *Third*, moving to better school districts is severely limited by low housing mobility and car ownership in Hungary. Homeownership patterns make moving difficult: only 8.3 percent of the population (and 7.7 percent of the households with dependent children) live as tenants (SILC, 2018), compared to a 30 percent mean in the EU and 36 percent in the US. (Eurostat 2024, Pew Research Center 2021). Owning a car available to transport children to school is also infrequent compared to developed countries. In our sample, 19 percent were given a car ride to school, and 4 percent went by school bus. Among low-status children (uneducated and/or unemployed parents), only 11-13 percent took a car, and 10-11 percent took a school bus.[10] Distance to good schools and public transportation deficiencies make moving to better schools difficult, especially for low-status children.[11] *Fourth*, a minority of students leave low-status, poor-performing schools after grade 6, and they potentially do so to escape from a crime-prone environment. An observable consequence of this 'white flight' is a fall in the number of students between grades six and eight, parallel with worse test results in grade eight than in grade six. We find that 38 percent of the non-incarcerated and 37 percent of the incarcerated students attended such schools. Regarding the fifth point, we can neither accept nor reject the assumption that exclusionary practices react to the presence of a crime-prone minority.

Bias from dichotomization. When we estimate the effect of school performance on incarceration probability, we would like to hold family background constant and vice versa. However, this condition does not necessarily hold when we work with a simple 2x2 typology (Table 7). In reality, the test performance indicators of good-performing schools, for instance, vary with the social background of their studentry (0.62 versus 0.39 in column 4), and the family background indicators of high-status schools vary with their test performance (0.37 versus 0.24 in column 5).

[10] The data relate to students filling in the NABC background questionnaire. Note that while school buses exist in rural areas, a US-style bussing policy and network does not exist in Hungary.

[11] Károlyi and Kertesi (2021) studied settlements with only one school in rural areas. They found that 1/2 of the children of highly educated parents and 1/10 of those from uneducated families attended a school outside their settlement of residence.

Table 7. Mean test and family background indicators and their differences across school types

High-status and low-status schools compared by test performance							Good-performing and poor-performing schools compared by family background						
School types		G	t (test)	f (f.b.)	t_{12}-t_{11} t_{22}-t_{21}	f_{12}-f_{11} f_{22}-f_{21}	School types		G	t (test)	f (f.b.)	t_{21}-t_{11} t_{22}-t_{12}	f_{21}-f_{11} f_{22}-f_{12}
high	good	11	0.62	0.37			high	good	11	0.62	0.37		
high	poor	12	-0.39	0.24	-1.01	-0.13	low	good	21	0.39	-0.27	-0.23	-0.64
low	good	21	0.39	-0.27			high	poor	12	-0.39	0.24		
low	poor	22	-0.60	-0.56	-0.99	-0.21	low	poor	22	-0.56	-0.56	-0.17	-0.80

G=identifiers of the four groups of schools
high, low = below-average and above-average values of the family background indicator
good, poor = below-average and above-average reading scores
t =mean standardized reading test score relative to the district mean
f = mean first principal component of the family background variables relative to the district mean
t_{12}-t_{11} (etc.): The subscripts relate to the school types (G)

To see the consequences, take the example of estimating the effect of test scores on the probability of imprisonment in the range of high-status schools. We estimate the probability difference between groups G_{12} (poor-performing, high-status schools) and group G_{11} (good-performing, high-status schools). In such an equation, $f_{12} - f_{11}$would ideally be zero. Since $f_{12} \neq, f_{11}$, we have Eq. (2), written here in a linear form:

[2] $p|G_{12} - p|G_{11} = (t_{12} - t_{11})\frac{dp}{dt} + (f_{12} - f_{11})\frac{dp}{df} = -1.01\frac{dp}{dt} - 0.13\frac{dp}{df}$

The first term is the 'true' effect of test performance, while the second is a bias component. Thus, the equations with school-type dummies do not precisely capture the marginal effects of school performance and family background on incarceration. However, the bias components have a much lower weight than the 'true effects' in each pairwise comparison.

Bad controls. Bad controls (Angrist & Pischke, 2014; Cinelli et al., 2020) appear as explanatory variables in a model but might also be dependent variables. Indicators of non-compliance, like absence on the test day and failure to fill in the background questionnaire, are clear examples. Exemption from testing may also indicate unfitting behavior. A poor grade in mathematics relative to one's test performance can also hint at a confrontational relationship between the student and the teacher (or outright discrimination).[12] Being older than 16 at the testing date may indicate a failure of integration correlated with later failures contributing to a criminal record. We will show that dropping these controls from the equations leaves the coefficients on school quality and exclusionary practices unchanged.

[12] Appendix Figure A1 shows that future prisoners achieve lower grades than their non-incarcerated counterparts, holding test performance constant. Using survey data, Kisfalusi et al. (2021) demonstrate a similar gap between Roma and non-Roma students in Hungary.

8.1 Results - Benchmark model

The estimates of Eq. 1 for the broad and narrow estimation samples are presented in Table 8.

Table 8: Estimates of Eq. 1

Dependent variable:	Incarcerated at least once		Months in prison		Number of prison spells	
Estimation:	Firthlogit		OLS		Poisson	
Displayed:	odds ratios		coefficients		IRR	
Girl	0.10***	0.09***	-0.26***	-0.28***	0.09***	0.08***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Multiple social disadvantages[b]	3.12***	3.03***	0.46***	0.44***	2.95***	2.82***
	(0.34)	(0.34)	(0.09)	(0.09)	(0.38)	(0.38)
SEN student, tested[b]	0.72	0.65*	-0.09	-0.12	0.76	0.71
	(0.16)	(0.16)	(0.09)	(0.10)	(0.19)	(0.19)
Mathematics grade/class mean[b]	0.23***	0.21***	-0.23***	-0.26***	0.28**	0.24***
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)
Mathematics grade missing	0.07*	0.08*	-0.50***	-0.52***	0.00***	0.00***
	(0.10)	(0.11)	(0.07)	(0.10)	(0.00)	(0.00)
Overage (past 16)	2.67***	2.31***	0.23***	0.16	2.85***	2.35***
	(0.36)	(0.33)	(0.09)	(0.10)	(0.41)	(0.36)
Did not fill out the questionnaire	1.73***	1.69***	0.07***	0.07***	1.82***	1.76***
	(0.20)	(0.20)	(0.03)	(0.03)	(0.22)	(0.22)
Absent on the day of the test	2.94***	2.78***	0.56***	0.58***	3.14***	2.88***
	(0.40)	(0.40)	(012)	(0.13)	(0.48)	(0.45)
SEN student, not tested[b]	3.97***	3.13***	1.08***	0.90**	3.89***	3.01***
	(0.81)	(0.70)	(0.38)	(0.42)	(0.85)	(0.72)
Crime rate (district level)[c]	1.26***	1.21***	0.05**	0.04*	1.23***	1.19**
	(0.08)	(0.08)	(0.02)	(0.02)	(0.09)	(0.09)
Class repetition rate		4.34***		1.15***		5.46***
		(2.40)		(0.44)		(3.18)
Separate classes for low-achievers		2.03***		0.32**		1.67**
		(0.40)		(0.13)		(0.37)
No group tutoring outside lessons		1.41***		0.04		1.23
		(0.18)		(0.05)		(0.16)
School type[a]						
#11 – High status, good performance	ref.	ref.	ref.	ref.	ref.	ref.
#12 – High status, poor performance	1.03	0.95	-0.05	-0.04	1.14	1.09
	(0.17)	(0.16)	(0.03)	(0.04)	(0.22)	(0.22)
#21 – Low status, good performance	0.90	0.86	-0.00	-0.02	0.95	0.91
	(0.15)	(0.15)	(0.03)	(0.03)	(0.17)	(0.17)
#22 – Low status, poor performance	2.02***	1.75***	0.17***	0.10**	2.03***	1.78***
	(0.24)	(0.22)	(0.04)	(0.04)	(0.26)	(0.24)
School type missing	1.25	4.32	0.06	2.07	1.44	4.46***
	(0.34)	(2.42)	(0.05)	(1.57)	(0.44)	(2.15)
Constant	0.02	0.02	0.30	0.31	0.02	0.02
Wald chi2, R^2	948.6	880.1	0.014	0.016	8053.9	5659.1
Observations	50,513	44,172	50,513	44,172	50,513	44,172

Robust standard errors are in parentheses. Significant at the *10, **5, and ***1 percent level

a) School typology based on 8-grade reading test scores and the first principal component of family background indicators

b) For the definitions of these indicators, see Appendix B.

c) District residents incarcerated in 2003-2017 per ten thousand inhabitants, on average in this period.

The table presents logit odds ratios [d(p/(1-p))/dX where p is the probability of a positive outcome] in the left block of the table, regression coefficients in the second, and incidence rate ratios (IRR) in the third one. The IRR coefficient says that for a unit change in the predictor variable, the difference in the logs of expected counts is expected to change by the respective coefficient. Given that more than 70 percent of the students had only one prison spell, the IRR-s and the odds ratios are close to each other.

Starting with two examples, *being absent* from the NACB tests nearly triples the odds of being incarcerated at least once. It increases the time spent in prison by more than half a month – a strong effect in a population spending 0.2 months on average behind bars. It also triples the difference in the logs of expected prison spells. *Girls'* odds of being incarcerated amounted to about 1/10 compared to boy's. They spent about ¼ months shorter time behind bars. The gender differential in the logs of expected prison spells was also substantial, about 1 to 11.

The most powerful predictors in Eq. 1 included being older than 16 on the test date, being socially disadvantaged, absent on the test day, and being exempted from testing (the odds ratios and incidence rate ratios range between 2.3 and 4.0 in columns 1 and 2, and 5 and 6). We got slightly lower estimates for those not filling out the background questionnaire and those attending schools that run separate classes for low-achievers and provide no group tutoring outside classes. SEN students who were tested had an average risk of incarceration. Those not tested had a very high incarceration rate. We observe no differences between high-status schools by test performance and good-performing schools by social background.

Turning to the effect of continuous variables, the odds ratios indicate a negative effect of the mathematics grade relative to the class mean, a moderately positive impact of the local crime rate, and a strong positive effect of the school-level grade repetition rate. The magnitudes are easier to assess using the marginal effects A one-standard-deviation lower maths grade predicts a 0.47 percent higher risk of imprisonment, nearly half of the average risk. Similarly calculated impacts of the grade repetition rate and the local crime rate amount to 0.1 percent (Appendix Table A5).

Table 9: Tests of pairwise equality of the parameters on school types

Dependent variable:	Incarcerated at least once		Months in prison		Number of prison spells	
Estimation	Firthlogit		OLS		Poisson	
Compared[a]	odds ratios		coefficients		IRR[c]	
Controls[b]	A	A+B	A	A+B	A	A+B
Estimated effect of test performance in high-status and low-status schools (Eq.1)						
- high-status schools	1.03	0.95	-0.00	-0.04	1.14	1.09
(test β12 - β11 = 0)	(0.17)	(0.16)	(0.03)	(0.04)	(0.22)	(0.22)
- low-status schools	2.25***	2.03***	0.17***	0.12***	2.15***	1.95***
(test β22 - β21 = 0)	(0.35)	(0.33)	(0.04)	(0.04)	(0.36)	(0.34)
Estimated effect of family background in good-performing and poor-performing schools (Eq.1)						
- good-performing schools	0.90	0.86	-0.00	-0.02	0.95	0.91
(test β21 - β11 = 0)	(0.15)	(0.15)	(0.03)	(0.03)	(0.17)	(0.17)
- poor-performing schools	1.96***	1.84***	0.17***	0.13***	1.78***	1.64***
(test β22 – β12 = 0)	(0.30)	(0.29)	(0.04)	(0.04)	(0.32)	(0.31)

Robust standard errors in parentheses. Significant at the *10, **5, and ***1 percent level

a) The abbreviations stand for 11—High status, good performance, 12—High status, poor performance, 21—Low status, good performance, and 22—Low status, poor performance.

b) Controls A: person-level and school-type controls. Controls A+B: further controls on exclusionary practices.

c) IRR = incidence rate ratios

In Table 9, we test the equality of the coefficients on school types using Stata's *lincom* procedure. The effect of test performance is stronger if the fraction of low-status children is high, and conversely, family background has a more robust effect in the zone of bad schools.

8.2. Alternative specifications and robustness checks

First, we re-estimated Eq.1. using an alternative measure of school-level test performance, T_{jk}/T_k, where T_{jk} is the mean 10th-grade test score of the graduates of primary school *j* attending secondary school *k*, and T_k is the mean test score of secondary school *k*. We expect that this measure is not as strongly correlated with the family background indicator (F_j) of primary school *j* as its contemporaneous school performance (T_j). In fact, $r(F_j,T_j)=0.59$ while $r(F_j,T_{jk}/T_k)=0.58$. If anything, the coefficients of the school-type dummies can be affected – this is tested in Table 10.

Table 10: Tests of pairwise equality of the parameters on school types using alternative indicators of test performance

Dependent variable:	Incarcerated at least once		Months in prison		Number of prison spells	
Estimation	Firthlogit		OLS		Poisson	
Compared[a]	odds ratios		coefficients		IRR[b]	
Test performance (grade)[c]	8^{th}	10^{th}	8^{th}	10^{th}	8^{th}	10^{th}
Estimated effect of test performance in high-status and low-status schools						
- high-status schools	0.95	0.88	-0.04	-0.03	1.09	1.23
(test β12 - β11 = 0)	(0.16)	(0.13)	(0.04)	(0.02)	(0.22)	(0.21)
- low-status schools	2.03***	1.32*	0.12***	0.15**	1.95***	1.60***
(test β22 - β21 = 0)	(0.33)	(0.19)	(0.04)	(0.07)	(0.34)	(0.29)
Estimated effect of family background in good-performing and poor-performing schools						
- good-performing schools	0.86	1.14	-0.02	0.03	0.91	0.98
(test β21 - β11 = 0)	(0.15)	(0.18)	(0.03)	(0.04)	(0.17)	(0.16)
- poor-performing schools	1.84***	1.71***	0.13***	0.22***	1.64***	1.28*
(test β22 – β12 = 0)	(0.29)	(0.26)	(0.04)	(0.06)	(0.31)	(0.19)

Robust standard errors in parentheses. Significant at the *10, **5, and ***1 percent level

a) The estimates are compared with Stata's l*incom* procedure. The abbreviations stand for 11—High status, good performance, 12—High status, poor performance, 21—Low status, good performance, 22—Low status, poor performance.

b) IRR: incidence rate ratios

c) 8^{th}-grade: school-level mean test score of primary school *j*. 10^{th}-grade: mean 10th-grade test score of the graduates of primary school *j* attending secondary school *k*, divided by the mean test score of secondary school *k*

The qualitative results of the models with the benchmark and alternative test performance indicators are similar. However, the differences between the compared coefficients are smaller in the logit and Poisson equations when the alternative indicator is used. This is not the case with the OLS for months in prison.

Second, we reestimated Eq.1 after dropping potential 'bad controls'. As shown in Appendix Table A6, the effects of MSD and the school's grade repetition rate appear stronger in the reduced model, while other coefficients are unaffected.

Third, despite the earlier concerns, we estimate the logit model of Equation 1 by replacing the school-type dummies with continuous measures of school performance, family background, and their interaction: F_j, T_j, and $F_j \times T_j$, with F and T normalized for the district means. We then calculate the average marginal effects of T at different levels of F and vice versa. The plots of Appendix Figure A2 suggest that while the confidence intervals are wide, the patterns of a stronger effect of T in low-status schools and a stronger effect of F in poor-performing schools seem to hold.

Table 11. School level estimates –Average marginal effects

Dependent variable:	At least one student incarcerated		Total months in prison		Total number of prison spells		
Estimation:	Logit		OLS		Poisson		Mean
Displayed:	odds ratios		coefficients		IRR		st.dev.
Share of girls	-0.19***	-0.19***	-7.03***	-6.72***	-0.25***	-0.24***	0.48
	(0.04)	(0.05)	(1.99)	(2.11)	(0.06)	(0.06)	(0.39)
Share of tested SEN	0.08	0.03	3.09	3.23	0.15*	0.07	0.03
students[a]	(0.07)	(0.09)	(3.70)	(4.40)	(0.09)	(0.12)	(0.08)
Fraction tested but not	-0.04	-0.05	-0.83	-1.64	-0.02	-0.03	0.23
filling the questionnaire	(0.04)	(0.05)	(1.27)	(1.46)	(0.05)	(0.06)	(0.55)
Fraction absent on the	0.34***	0.34***	24.5***	20.8***	0.49***	0.45***	0.06
day of the test	(0.07)	(0.08)	(6.19)	(6.47)	(0.10)	(0.11)	(0.09)
Share of SEN students	0.16*	0.20*	9.54**	11.00*	0.26***	0.26**	0.02
not tested	(0.10)	(0.12)	(4.22)	(6.02)	(0.10)	(0.12)	(0.07)
Crime rate (district level)[c]	0.06***	0.05***	1.58***	1.07**	0.08***	0.07***	1.78
	(0.01)	(0.01)	(0.47)	(0.53)	(0.01)	(0.01)	(0.67)
Class repetition rate	..	0.41***	..	30.3***	..	0.18	0.03
		(0.18)		(10.0)		(0.14)	(0.04)
Separate classes	..	0.14***	..	8.16*	..	0.15***	0.03
for low-achievers		(0.04)		(4.4)		(0.05)	
No group tutoring	..	0.05***	..	2.25*	..	0.10***	0.16
outside lessons		(0.02)		(1.22)		(0.03)	
11 – High status, good performance	ref.	ref.	ref.	ref.	ref.	ref.	0.31
12 – High status, poor	-0.00	-0.02	0.04	-0.75	-0.00	-0.04	0.15
performance	(0.02)	(0.02)	(0.80)	(0.80)	(0.03)	(0.03)	
21 – Low status, good	-0.01	-0.03	-0.39	-1.21	-0.02	-0.05	0.18
performance	(0.02)	(0.02)	(0.70)	(0.80)	(0.03)	(0.03)	
22 – Low status, poor	0.10***	0.06***	3.10***	1.51*	0.15***	0.11***	0.35
performance	(0.02)	(0.02)	(0.75)	(0.87)	(0.03)	(0.03)	
School type missing	-0.05	-0.16***	-4.94	-14.9**	-0.11***	-0.19***	0.01
	(0.06)	(0.02)	(3.01)	(6.73)	(0.04)	(0.03)	
Baseline odds/Constant	0.12	0.15	2.19	2.75	0.12	0.15	
Wald chi2, R^2	139.9***	132.0***	0.056	0.067	176.7***	179.7***	
Observations	2,441	2,132	2,441	2,132	2,441	2,132	
Mean (st.dev.) of the dependent variable	0.18	(0.39)	4.17	(14.9)	0.23	(0.55)	

Significant at the *) 10, **) 5, ***) 1 percent level.

a) SEN: special education needs. b) MSD: multiple social disadvantages

Finally, Table 11 presents the models estimated at the school level. We used a simple logit to estimate the probability of one or more future prisoners in the school since this is not a rare event. We dropped the share of overage students as it is strongly correlated with the grade repetition rate and the fraction of MSD students as it is closely related to the family background variable used for the school typology.

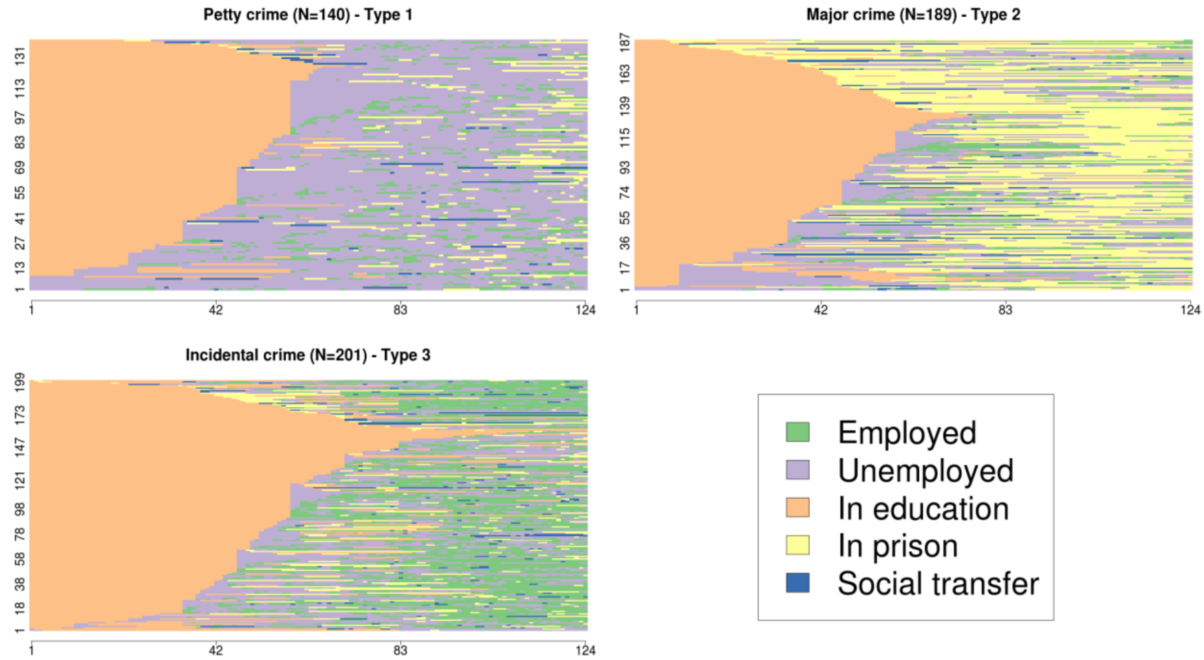
The shares of students absent on the test day or exempted from testing are powerful predictors in each model. A one-standard deviation difference in the repetition rate increases the likelihood of having at least one future prisoner by 1.6 percent and the time in prison by 1.2 months. A minority of schools separating the low-achievers or not providing tutoring have a 14 percent and 5 percent higher probability of issuing future prisoners, respectively, and add 8 and 2 months to the school sample's prison record. The parameters of the school-type dummies are similar to those estimated at the student level.

8.3 Career path heterogeneity

Using all the information in our dataset, we can analyze it as categorical sequence data. For each month, we define one state that best describes the given individual's situation. We create sequences using five mutually exclusive states (in school, in prison, employed, non-employed and receiving some transfer, non-employed without any of the above) for 124 months. We restrict the sample to individuals who were incarcerated during our time window. Using the Ward clustering method proposed by Gabadino et al. (2011) for R users (TraMineR), we cluster the status histories into three types, grouping together the most similar ones through minimizing within-cluster variation.

Figures 3 and 4 represent the three clusters provided by the algorithm. These correspond to three distinct patterns and potentially reflect criminal activities of different natures. Figure 3 displays individual state sequences (each horizontal bar represents a single person's career), while Figure 4 shows the distribution of cluster members in each month. Appendix Table A7 adds supplementary information on the characteristics of the clusters.

Figure 3: Individual state sequences in 2008-2017



Source: Ward clustering results. The number of observations in the three clusters are 140, 189, and 201, respectively. X axis represents months passed since taking the 8th grade NABC test.

Type 1 persons tend to leave education early and predominantly enter unemployment immediately after school. Their time as unemployed is interrupted by short prison spells (Figure 1). Less than ten percent of the group members are incarcerated at any point except for the end of the observation period when this fraction grows to about twenty percent. Their employment also increases mildly but only slightly exceeds ten percent, even at the end of the time window (Figure 2). The members of this group are more likely to be exempted from the NABC, perform poorly if they write the tests, are much less likely to be employed, and earn significantly less than their Type 2 and Type 3 counterparts. We are tempted to label this group as the 'petty crime' type.

Type 2 people's school careers are similar to their Type 1 counterparts. However, many of them go to jail right after exiting from education, and their incarceration spells are much longer (Figure 1). Being imprisoned is the most frequent status after leaving school: in the second part of the time window, 50-70 percent of the cluster members are incarcerated (Figure 4). Recidivism is more frequent in this group, and the average duration of completed prison spells amounts to 26 months compared to 4 and 6 in the other two clusters. The group members perform better at the cognitive tests, are slightly more likely to be employed, and earn almost 20 pp higher wages than Type 1 people. The data hint at a high proportion of severe offenses in this 'major crime' group.

Figure 4: Distribution by states in the three clusters over time in 2008-2017

Source: Ward clustering results. The number of observations in the three clusters are 140, 189, and 201, respectively. X axis represents months passed since taking the 8th grade NABC test.

Type 3 students performed significantly better on the 8th-grade tests than the other two groups. They typically experience a single prison spell. Some continue their studies even at the end of the time window. They are much more likely to be employed (50 percent compared to 12 and 22 in the other two clusters) and earn 30 pp and 20 pp higher relative wages than Type 1 and Type 2 people, respectively. It is hard to find a meaningful label for this group – given its members' low recidivism rate and better school and labor market performance, we will call the group 'accidental.' We now reestimate the incarceration equations by distinguishing the three groups.

Table 12. Multinomial logit estimates of career path cluster membership and tests of pairwise equality of the parameters on school types

Clusters (assumed crime type)	1 (Petty)	2 (Major)	3 (Incidental)
Girl	0.10***	0.06***	0.08***
	(0.03)	(0.02)	(0.02)
SEN student, tested	1.38	1.06	0.74
	(0.50)	(0.37)	(0.29)
Overage (past 16)	1.80**	1.73**	2.51***
	(0.50)	(0.43)	(0.54)
Multiple social disadvantages (MSD)	5.09***	4.50***	4.89***
	(1.08)	(0.83)	(0.85)
Class repetition rate	9.36***	5.34*	0.75
	(7.47)	(4.64)	(0.69)
Separate classes for low-achievers	1.76	2.44***	1.79*
	(0.66)	(0.72)	(0.59)
No tutoring outside classes	1.72**	1.24	1.52**
	(0.37)	(0.28)	(0.30)
School types[a]			
High-status, poor-performing	1.04	1.19	0.76
	(0.33)	(0.38)	(0.20)
Low-status, good-performing	1.02	1.22	0.61*
	(0.32)	(0.64)	(0.17)
Low-status, poor-performing	1.68**	2.71***	1.39**
	(0.41)	(0.63)	(0.25)
School type missing	4.06	16.75***	0.00***
	(3.83)	(11.65)	(0.00)
Constant	0.002	0.002	0.005
High-status and low-status schools compared by the estimated effect of test performance (Eq 1)[b]			
- high-status schools	1.04	1.19	0.76
(H0: $\beta_{12} - \beta_{11} = 0$)	(0.33)	(0.38)	(0.20)
- low-status schools	1.65*	2.22***	2.28***
(H0: $\beta_{22} - \beta_{21} = 0$)	(0.47)	(0.58)	(0.61)
Good-performing and poor-performing schools compared by the estimated effect of family background (Eq1)[b]			
- good-performing schools	1.02	1.22	0.61*
(H0: $\beta_{21} - \beta_{11} = 0$)	(0.31)	(0.37)	(0.17)
- poor-performing schools	1.62	2.26***	1.81**
(H0: $\beta_{22} - \beta_{12} = 0$)	(0.48)	(0.62)	(0.47)

Relative risk ratios and standard errors. Significant at the *10; **5; ***1 percent level. Pseudo $r^2 = 0.116$
Observations: 44,172. Positive outcomes. Petty: 129. Major: 161. Incidental: 178.
a) School typology based on 8-grade reading test scores and the first principal component of family background indicators relative to the district means. Students attending high-status, good-performing schools are the reference category.
b) The estimates are compared with Stata's *lincom* procedure. The abbreviations stand for 11 – High status, good performance. 12 – High status, poor performance. 21 – Low status, good performance. 22 – Low status, poor performance.

The effects of school types familiar from estimates for the entire sample appear in the cluster-level results. However, they seem to be strongest for cluster 2, assumed to collect cases of major crime, and weakest for the petty crimes group.

10. Discussion and conclusions

We studied linkages between school-level test performance and peer characteristics, exclusionary practices, and non-compliance on the school and student levels, on the one hand, and several indicators of students' later incarceration on the other. The data related to 14-15-year-old primary school students followed until age 23-24, with slightly more than one percent of them incarcerated at least once in this age range.

The imprisonment probabilities predicted by our models vary widely. The prediction for a boy studying in a low-status, good-performing school is 0.5 percent at other explanatory variables' mean or default value. A similar boy in a low-status, poor-performing school has a probability of 1.0 percent. Being absent on the test day increases the prediction to 2.8 percent. The probability rises to 8.1 percent if the school's class repetition rate is twice the average, runs separate classes for low-achievers, and provides no tutoring.[13] Our estimates arguably capture more than just (potentially spurious) correlations.

First, we argued that exposure to school quality and practices is mainly exogenous for the student population susceptible to imprisonment. The rules of primary school enrolment and the patterns of home and car ownership limit a sharp response to the expected or actual presence of a crime-prone minority (within the low-status studentry we control for). The feedback from crime-proneness to teaching quality and peer composition is rendered weak. However, exclusionary practices may potentially respond to the disciplinary problems related to unobserved family and neighborhood characteristics of future offenders. Student non-compliance can be regarded as an early signal (rather than a cause) of later conflict with the law. However, our estimates are weakly affected by excluding the respective variables.

Second, the literature uncovered several paths from poor-performing and/or intolerant schools to delinquency. These schools issue graduates with inferior skills that supply low returns to employment relative to crime. Future prisoners are more likely to attend schools dominated by low-status children, providing no tutoring, having separate classes for low-achievers, and high grade repetition rates. Less contact with high-status and/or good-performing peers confines them in building non-cognitive skills essential for labor market success (Bowles and Gintis, 1976, Heckman and Rubinstein, 2001, Heckman et al., 2006). Rejection in the form of 'flunking', no coaching after classes, and getting substandard education in special classes undermine dependability and conformity. Indeed, most of them enter the labor market as unemployed and have scattered employment histories. Their jobs are typically short, often within public and casual work programs, which ensure no long-lasting cooperation with successful peers.

A weakness of our analysis to be admitted is the lack of person-level information on ethnicity. The practice of routing disadvantaged children to low-quality schools and classes affects Hungary's sizeable Roma minority disproportionately. Relying on survey data, Havas (2008) estimated that while there was a twofold increase in the share of Roma children in primary schools between 1980 and 2003, the number of hundred percent Roma classes grew by a factor of eight. Furthermore, he found the share of Roma children to be 30 percent in standard classes, 15 percent in special classes for high achievers, and 70 percent in special classes for low achievers in 2003. Setting up a different school building for Roma pupils is a common practice, as is grading discrimination that we touched upon earlier. The role of 'racially' biased treatment remains one of the unanswered questions in this paper. Further issues we

[13] We calculated these predictions using the coefficients (β) underlying the odds ratios in the second column of Table 8 (narrow estimation sample), setting the values of the explanatory variables (X) by choice and taking the inverse of the logit function at $\Sigma X\beta$.

could not address with the data to hand include unobserved individual characteristics directly affecting both schooling and criminal decisions, a distinction between involvement in crime, arrest, conviction, and incarceration, or an individual-level analysis of the student's family background.

Notwithstanding these weaknesses, we could draw attention to some under-researched areas. We could measure school quality using nationwide standardized test results rather than weak proxies like teacher wages, teacher tenure, or the teacher-student ratio. We could show that incarceration probabilities vary with test scores only in the zone of low-status schools. We could also show that even in the absence of strict 'zero tolerance' policies, some milder forms of exclusionary practices may have a strong effect on future conflicts with the law. Finally, we could demonstrate that student non-compliance is a good predictor (albeit hardly a cause) of later incarceration.

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Appendix A – Additional tables and figures

Table A1: Descriptive statistics of the estimation samples – Person and school level

	Estimation sample			
	Broad		Narrow	
Unit of observation: person				
Incarcerated at least once	.0098		.0106	
Time in prison (months)	.1770	2.694	.1889	2.792
Number of prison spells	.0133	.1499	.0143	.1551
Girl	.4865		.4823	
MSD	.0782		.0850	
SEN student, tested	.0283		.0292	
Math grade relative to the class mean	.9969	.3074	.9971	.3131
Math grade missing	.0030		.0028	
Overage (past 16 at the test date)	.0500		.0532	
Did not fill out the background questionnaire	.2385		.2351	
Was absent on the test day	.0517		.0527	
SEN student, not tested	.0104		.0104	
Crime rate (district level)	1.747	.6595	1.759	.6721
Class repetition rate (school-level)			.0539	.0660
Separate classes for low-achievers (school-level)			.0314	.1745
No tutoring outside lessons (school-level)			.1255	.3314
Studied in high-status, good-performing school	.4005		.3981	.4895
Studied in high-status, poor-performing school	.1327		.1406	.3476
Studied in low-status, good-performing school	.1596		.173	.3788
Studied in low-status, poor-performing school	.2602		.2864	.4521
School type missing	.0466		.0011	.0339
Observations	50,513		44,172	
Unit of observation: school				
At least one future prisoner in the school	.1720		.1838	
Months in prison	3.952	14.59	4.171	14.9
Number of prison spells	.2175	.5390	.2321	.5523
Share of girls	.4785	.1572	.4752	.1511
Share of SEN students tested	.0334	.0828	.0337	.0771
Fraction not filling out the background questionnaire	.236	.1757	.2333	.1704
Fraction absent on the test day	.0611	.0933	.061	.0908
Share of SEN students not tested	.018	.0777	.0177	.0664
Crime rate (mean of the district-level rates)	1.770	.6579	1.776	.6699
Class repetition rate	.0253	.0446	.0253	.0446
Separate classes for low-achievers	.0276		.0276	
No tutoring outside lessons	.1608		.1608	
High-status, good-performing school	.3523		.3095	
High-status, poor-performing school	.1487		.1543	
Low-status, good-performing school	.1683		.1819	
Low-status, poor-performing school	.3203		.3508	
School type missing	.0102		.0032	
Observations	2,441		2,132	

Abbreviations. MSD = multiple social disadvantages. SEN: special education needs

Table A2: Principal component analysis of the variables on family background – School level

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.4008	1.3596	0.4802	0.4802
Factor2	1.0411	0.4156	0.2082	0.6884
Factor3	0.6255	0.1349	0.1251	0.8135
Factor4	0.4906	0.0488	0.0981	0.9116
Factor5	0.4417	.	0.0884	1.0000

Method: principal-component factors. Two factors are retained.
Observations: 2,431 schools
LR test: independent vs. saturated: chi2(10) = 2627.48 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Uniqueness
Fraction of students with no working parent	0.7362	0.3830	0.3114
Fraction of students with no educated parent[a]	0.7799	0.3196	0.2896
Fraction of students with at least one highly educated parents[b]	-0.6589	0.4017	0.4045
Fraction of Roma students	0.7926	0.0956	0.3627
Fraction of Roma students unknown	-0.4341	0.7886	0.1897

a) No parent with higher than primary education
b) At least one parent has college/university attainment

Table A3: The distribution of districts by mean test performance and family background

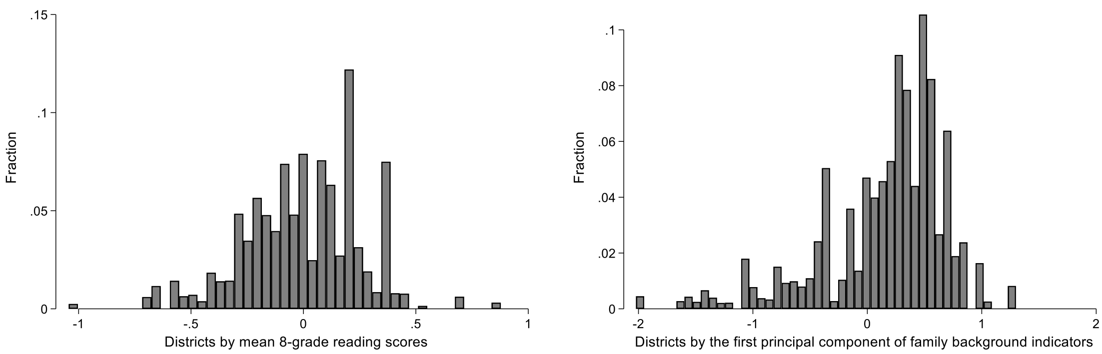


Table A4: Exclusionary practices and proxies on non-compliance by school types
(Percent, students in the cell=100)

	School types				
Family background:	High	High	Low	Low	All
Test performance:	Good	Poor	Good	Poor	schools
Class repetition rate	3.2	5.7	4.8	8.7	5.4
Separate classes for low-achievers	2.9	2.2	1.4	5.0	3.1
No group tutoring outside lessons	13.5	11.1	10.1	13.3	12.5
Background questionnaire unfilled	23.6	25.6	21.5	23.6	23.5
Absent on the day of the test	4.9	4.6	5.5	6.0	5.2
Exempt for behavioral deficiencies	0.5	0.9	0.9	1.7	1.0
Observations (students)	17,586	6,211	7,671	12,653	44,121

Sample: Students of schools that filled out the NABC Pilot Survey and the NABC Establishment Survey. The number of observations is lower than in the narrow estimation sample (N=44,172): 51 students have been dropped because the school type variable was missing. Equation 1 treats this using a dummy for missing cases.

Table A5: Marginal effects from Eq. 1.

	Estimation sample			
	Broad		Narrow	
	b	std. error	b	std.error
Girl	-.0217	.0017	-.0244	.0020
Overage (past 16)	.0091	.0012	.0084	.0014
SEN student, tested	-.0031	.0020	-.0042	.0023
MSD	.0149	.0019	.0153	.0021
Relative math grade	-.0137	.0016	-.0158	.0018
Math grade missing	-.0247	.0135	-.0253	.0140
Did not fill out the background questionnaire	.0051	.0010	.0052	.0011
Was absent on the test date	.0100	.0013	.0100	.0014
SEN student, not tested	.0129	.0019	.0114	.0022
Crime rate (district)	.0021	.0005	.0019	.0006
Grade repetition rate (school)	.	.	.0147	.0055
Separate classes for low-achievers	.	.	.009	.0030
No tutoring outside lessons	.	.	.0038	.0015
Studied in high-status, good-performing school	ref.	ref.	ref.	ref.
Studied in high-status, poor-performing school	.0002	.0012	-.0004	.0013
Studied in low-status, good-performing school	-.0007	.0011	-.0011	.0012
Studied in low-status, poor-performing school	.007	.0011	.0059	.0010
School type missing	.0017	.0023	.0243	.0150

See Table 8 for the test statistics

Table A6: Estimates of Equation 1 without the possibly bad controls

Dependent variable:	Incarcerated at least once		Months in prison		Number of prison spells	
Estimation:	Firthlogit		OLS		Poisson	
Displayed:	odds ratios		coefficients		incidence rate ratios	
Estimation sample	Broad	Narrow	Broad	Narrow	Broad	Narrow
Girl	0.09***	0.08***	-0.30***	-0.32***	0.08***	0.07***
	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)
Multiple social disadvantages (MSD)[b]	5.08***	4.69***	0.61***	0.57***	5.01***	4.46***
	(0.53)	(0.51)	(0.09)	(0.09)	(0.62)	(0.57)
SEN student, tested[b]	1.35	1.23	0.01	-0.02	1.38	1.30
	(0.27)	(0.26)	(0.08)	(0.09)	(0.29)	(0.29)
Crime rate (district level)[c]	1.25***	1.19***	0.04**	0.04	1.22***	1.17**
	(0.07)	(0.07)	(0.02)	(0.02)	(0.09)	(0.08)
Class repetition rate		6.44***		1.21***		9.06***
		(3.30)		(0.43)		(4.83)
Separate classes for low-achievers		1.99***		0.33**		1.68**
		(0.39)		(0.13)		(0.36)
No group tutoring outside lessons		1.43***		0.05		1.27*
		(0.18)		(0.05)		(0.16)
School type[a]						
High status, good performance	ref.	ref.	ref.	ref.	ref.	ref.
High status, poor performance	1.03	0.93	0	-0.04	1.14	1.06
	(0.17)	(0.16)	(0.03)	(0.04)	(0.22)	(0.21)
Low status, good performance	0.96	0.91	0.00	-0.02	1.02	0.96
	(0.16)	(0.15)	(0.03)	(0.03)	(0.19)	(0.18)
Low status, poor performance	2.18***	1.81***	0.18***	0.10***	2.25***	1.87***
	(0.25)	(0.22)	(0.04)	(0.04)	(0.29)	(0.25)
School type missing	1.19	6.61***	0.07	2.47	1.39	6.48***
	(0.32)	(3.63)	(0.05)	(1.55)	(0.43)	(2.77)
Constant	0.01	0.01	0.15	0.13	0.01	0.01
Wald chi2, R^2	687.8	668.0	0.009	0.011	737.7	788.6
Observations	50,513	44,172	50,513	44,172	50,513	44,172

Robust standard errors in parentheses. Significant at the *10, **5, and ***1 percent level

a) School typology based on 8-grade reading test scores and the first principal component of family background indicators

b) For the definitions of these indicators, see Appendix B.

c) District residents incarcerated in 2003-2017 per ten thousand inhabitants, on average.

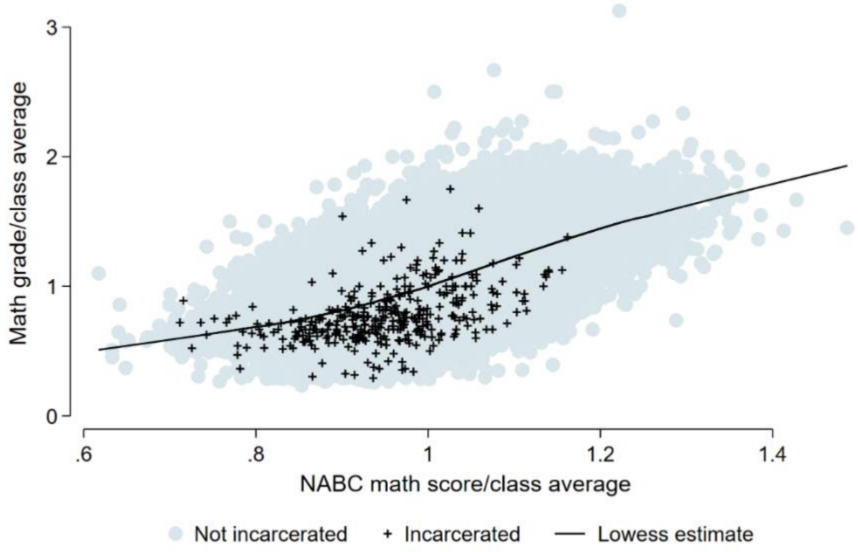
Possible bad controls include no background questionnaire, being absent on the test date, being exempted from testing, being overage (past 16), relative mathematics grade

Table A7: Selected indicators in the three clusters and the non-incarcerated population

	Clusters			
	(0)	(1)	(2)	(3)
Assumed crime type:	None	Petty	Major	Incidental
Personal characterisics in 2008				
Reading test score (standardized)	0.01	-1.22	-1.08	-0.98
Mathematics test score (standardized)	0.01	-0.87	-0.88	-0.69
No parent with higher than primary education %	5.6	16.4	10.6	12.9
No working parent %	5.7	13.6	12.7	9.9
At least one parent has tertiary education %	20.4	0.7	3.2	3.5
School characteristics in 2008				
Mean reading test score (standardized)	0.16	-0.53	-0.61	-0.31
Family background, first principal component	0.17	-0.50	-0.58	-0.26
Grade repetition rate %	6.7	13.8	17.4	11.2
Separate classes for low-achievers %	3.1	5.8	8.7	5.4
No group tutoring outside classes %	12.6	23.3	16.2	19.5
Roma share (if non-missing) %	12.5	25.1	28.4	20.9
After school				
Age at leaving education	21.2	18.3	18.5	19.3
Left school before age 18 %	1.4	10.7	18.0	6.4
Age at first incarceration	..	22.1	19.9	21.3
Number of prison spells	..	1.3	1.6	1.2
Months in prison	..	6.0	39.2	7.0
Months in school or employment[a]	105.6	54.6	61.9	90.3
Log monthly earnings[b]	ref.	-0.58	-0.35	-0.16
Log monthly earnings within occupation[c]	ref.	-0.32	-0.18	-0.12

a) If out of prison
b) Regression coefficients. Log monthly earnings regressed on crime type and month fixed effects
c) One digit ISCOR codes added.

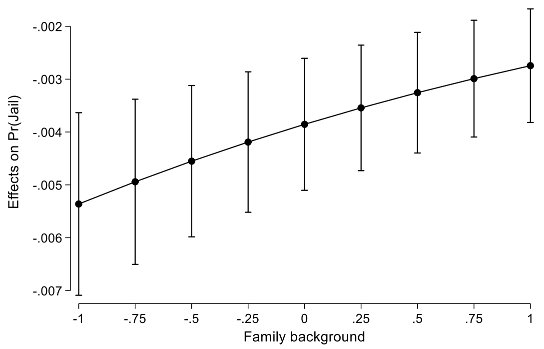
Figure A1: Grading discrimination: The relative mathematics grade and relative mathematics test score of future prisoners - Data relating to those writing the NABC tests

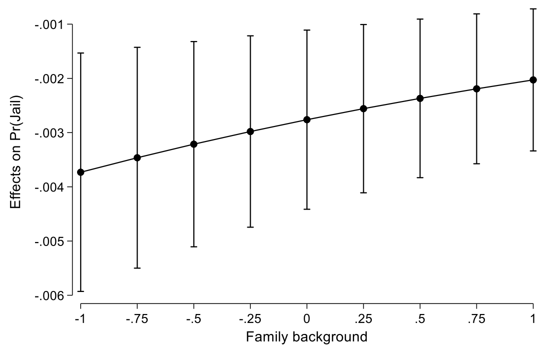


Appendix Figure A2: Main results from models with continuous school-level test scores, family background, and their interaction – Dependent variable: incarcerated at least once

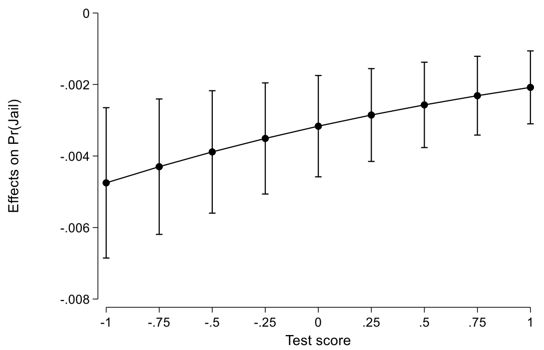
Broad estimation sample | Narrow estimation sample

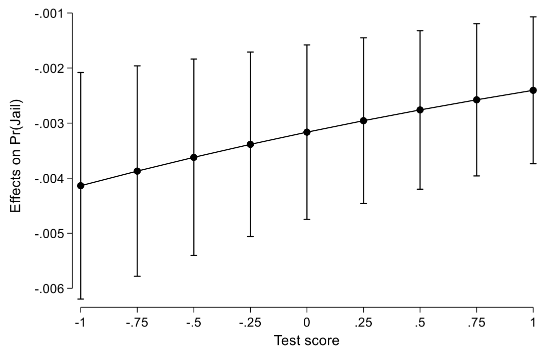
Average marginal effects of the test score at different levels of the family background indicator





Average marginal effects of the family background indicator at different levels of the test score





Appendix B: Definitions of selected control variables in Equation 1

Multiple social disadvantages (MSD). In our time window, a student could apply for an MSD status if at least two of the following three conditions held: i) The family head had at most primary education background, (ii) The family head was non-employed, (iii) The child lived in a sub-standard dwelling. The notary of the student's settlement approved or rejected the application. Students living in an orphanage or with foster parents were unconditionally eligible.

Special education needs (SEN). SEN status is examined and determined by an Expert Committee. The diseases and disturbances examined include dyslexia, dysgraphia, dyscalculia, mutism, conduct disorder, and learning disabilities (mental handicaps). SNI students were exempted from the NABC, but schools could decide to test them to help teachers evaluate their performance and examine their progress over time. The results of SEN students were excluded from the evaluation phase of NABC. As we mentioned in the text, pupils were often classified as SEN without proper medical justification.

Relative mathematics grade. In the NABC Pilot Survey, schools must report their students' mathematics grades achieved in the semester preceding the NABC tests. We calculated the grade of each student relative to the class mean.