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Banning Mobile Phones at Schools: Effects on Bullying and Academic Performance.

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Banning Mobile Phones at Schools: Effects on Bullying and Academic Performance.

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Abstract

We investigate the impact of banning mobile phones at schools on bullying incidence and students academic achievement, using as comparative case studies two regions in Spain whose autonomous governments established mobile bans as of year 2015. We apply diff-in-diff regression and the synthetic control method to analyse reported cases of bullying and PISA scores in maths and sciences, and compare each of the treated regions with the rest of regions in Spain before and after the intervention. We find that the mobile ban noticeably reduced bullying incidence, particularly among 12-to-14 year old kids and 15-to-17 year old adolescents. Also, using the results of five waves of the PISA assessment by region, we find positive effects of the mobile ban on the students' scores in maths and sciences. Our paper is one of the first to provide direct evidence on this highly debated topic.

Keywords: mobile phones, bullying, academic performance, comparative case studies.

JEL classification: C01; D91; I12; I18.

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1 Introduction

Should mobiles be banned in schools? This question is on the current agendas of education policy mandates, on the day-to-day work of school teachers, as well as on the mind of any parent with children at school-age, and has generated recent debates in many countries. Beyond particular policies at the individual school level, governments in some countries, such as France, Israel, or some states of Australia, banned mobiles in schools in recent years.[1] Instead, in 2015 the Mayor of New York removed a ten year ban of phones on schools, claiming that abolition could decrease inequality. While a correct use of these and other mobile devices can possibly enhance academic development and learning in some contexts, the use of mobile phones as a source of entertainment in schools can have detrimental effects on students' academic performance.

Two are the main goals that governments that recently banned these devices in schools are trying to achieve: reducing bullying and improving academic performance.[2] Despite the heated debate, the topic needs more attention from an academic perspective as there is scarce formal evidence on the consequences of mobile phones use in schools. This is especially important on primary and secondary education, since it is at this age when kids initiate the use of these devices.[3] Although there exists some evidence on the link between using mobiles and academic performance with college students (e.g., Lepp et al. 2014), research on the effects at the earlier educational stages is almost absent (an exception is Beland and Murphy, 2016). Besides this, and to our knowledge, direct evidence on the potential effects of regulating mobile use at schools on bullying is inexistent.

In this paper, we investigate the impact of banning mobile phones at schools on bullying incidence and students academic achievement. To this end, we use as comparative case studies two regions in Spain (Galicia and Castilla La Mancha, CLM henceforth) whose autonomous governments passed laws to ban mobiles in primary and secondary educational centers towards the end of year 2014 (CLM) and beginning of year 2015 (Galicia), while in the rest of Spanish regions the mobile use by students at schools is not regulated. These

[1] In France, the policy came into effect during the beginning of the 2018-2019 school year and impacted students over 15. Starting in 2019 there are already 4 States in Australia banning smartphones to students up to 18 years. Also in 2016, the Israeli Ministry of Education decided to ban mobiles during school day. https://typicalstudent.org/hot/lists/5-countries-banned-mobiles-gadgets-schools, last accessed 20 October 2020.

[2] The French government claimed that the new law would improve concentration in class, while helping to prevent cyber bullying and the viewing of pornography (BBC, 2018). In Australia, the Education Minister of Victoria state justified the approval of the law because 'This will remove a major distraction from our classrooms, so that teachers can teach, and students can learn in a more focused, positive and supported environment. Half of all young people have experienced cyberbullying. By banning mobiles we can stop it at the school gate' (Henriques-Gomes, 2019).

[3] In 2006, 58% of children between 10 and 15 years had a mobile phone in Spain, while this percentage rose to 66% in 2019. Furthermore, while in 2006 72% of children between those ages were internet users, in 2019 this percentage reached 93%.

prohibitions constitute a quasi-natural experiment that allows us to take the case of Spain and their regions as an excellent lab for the analysis of this highly debated policy.[4] This is because, although with their own idiosyncratic differences, the 17 autonomous regions of Spain (Comunidades Autónomas) share common historical determinants in terms of educational programmes, economic and political structures, and social norms, while each regional government is free to regulate some of the aspects of its educational system.

To conduct the analysis, we construct a region-level panel of data for our outcome variables of interest, as well as for several regional-year control variables, using official data sources for the 17-Spanish regions before and after the mobile bans (with the exceptions that we will comment below). For the analysis of bullying, we apply diff-in-diff regression to our outcome variables, which are officially reported cases for every 10,000 school students in four age intervals (covering from 6 to 17 year olds), spanning over the period from 2012 to 2017. The information on reported cases by region and year was requested to the Spanish police forces and made public by the Spanish Ministry of Education in 2018, following a specific demand of information in this regard made by a member of parliament. Thus, the region-year-age level data on bullying used in this paper is quite unique, and there no exist to our knowledge any other paper that has exploited variation across regions (or other units), years and age intervals on bullying cases to perform our kind of analysis.

For the analysis of academic outcomes, we use the scores obtained by Spanish students in the five PISA assessments conducted from 2006 to 2018 (every 3 years). As participation in the PISA calls is not mandatory, the CLM region did not participate in the calls of 2006 and 2012, which poses us with problems for the analysis of the pre-intervention trends in the academic achievement of students in this region. Thus, we take with special caution the analysis of the academic outcomes in the case of the CML region. The data for the Galicia region is nevertheless complete, and taking advantage of this we complement the diff-in-diff regression analysis with the application of the synthetic control method (SCM, henceforth, Abadie and Gardeázabal, 2003; and Abadie et al. 2010) to evaluate the impact of the mobile ban on students' PISA scores in this region.[5]

The use of mobile devices is not necessarily detrimental for education when correctly designed. For example, the use of certain Apps could make children more involved in their learning process and increase the enjoyment from studying. In addition, the immediate access to an infinite source of information can complement instruction received at schools and improve the learning process of students (Milrad, 2003). Furthermore, students can rapidly share information not only with other students, but also with teachers, which could lead to a more efficient studying and collaboration (Chen and Ji, 2015; Lepp, et al., 2015).

Positive effects on academic achievement can also come from potential complementarities

[4]The government of the region of Madrid announced mobile bans at schools for academic year 2020-21.
[5]The pre-intervention length of the series of data on bullying is not large enough as to apply the SCM.

between the use of mobiles and the development of other technological competencies on the part of students, provided that the later enhance academic outcomes. In this regard, our paper is also related to the literature on the impact of technology on students' outcomes. Results from this literature, however, are far from conclusive.[6] Some results seem to indicate that what actually matters is not the technology on its own, but rather the structured or unstructured use of a particular technology. For instance, Barrow et al. (2009) find that students randomly assigned to computer-aided instruction, using an algebra program, largely improve on algebra test scores compared to the students receiving traditional instruction. Also, Muralidharan et al. (2019), show that well-designed, technology-aided instruction programs sharply improve test scores in middle-school grades.[7]

Unfortunately, we do not have information about the specific use that students are giving to smartphones in schools. However, even if mobile phones are used to structured activities, allowing them in schools opens the door to be used for recreational purposes as well, thus generating distraction. In fact, according to research in computer science and educational studies, the detrimental effects of mobile phones in schools are explained because multitasking or task-switching decrease learning (Jacobsen and Forste, 2011; Junco and Cotten, 2011, 2012; Rosen et al., 2013; Wood et al., 2012). For example, notifications on the smartphone are a constant distraction limiting students' attention during class and/or study time (Junco and Cotten, 2012). Besides, the desire to continuously interact with the rest of the world may lead to a level of concentration that is lower than needed to achieve a good study performance (Chen and Yan, 2016).[8] Finally, unmotivated students have a great temptation at their fingertips to switch off from the lesson and play games, surfing the internet or use social networks (Hawi and Samaha, 2016). Some experimental papers present additional evidence pointing in this direction (see, e.g., Wood et al., 2012; Kuznekoff and Titsworth; 2013; Levine et al., 2013; see also Amez and Baert, 2020, for a survey of papers published in this field).[9]

Research on the relationship between the use of cell phones in schools and bullying is even scarcer. A possible explanation for this lack of studies is the difficulty in obtaining

[6]Fiorini (2010), Fairlie (2005) and Malamud and Pop-Eleches (2011), find large positive effects of home computers on educational outcomes, while Fuchs and Woessmann (2004) and Vigdor et al. (2014) find evidence of negative effects of home computers on educational outcomes. Fairlie and Robinson, (2013) do not find significant effects of owning a computer on any educational outcome.

[7]Additional complementary uses of mobile technology in education have been studied, for instance, by Bergman, 2020, who shows that providing information via text message, phone calls or emails to parents about their children's academic progress, produce gains to student effort and achievements.

[8]The need not to miss out what is happening in internet has been labelled as FOMO, 'fear of missing out'.

[9]Wood et al. (2012) set up an experiment where participants were randomly assigned to either a multitasking environment (using one of these technologies: texting, e-mail, Facebook or MSN messaging), or to a no multitasking environment, while participating in classroom learning activities. After the lesson, a multiple-choice test was used to assess learning. Results showed that multi-tasking with any of the technologies had a negative impact on learning.

reliable data on bullying cases. The link between cell phones in schools and bullying is very intuitive. Given that cyberbullying already represents 20% of bullying cases (Cook, 2020) and that smartphones are one of the main conduits for cyberbullying among children (Adams, 2019), the removal of the instrument should be expected to influence the number of bullying cases.

The closest paper to our study is Beland and Murphy (2016). They investigate the impact of banning mobile phone use in schools on student academic results using a sample of 91 schools in four English cities. In particular, they analyse the gains in test scores across and within schools before and after mobile phone bans were introduced, and find positive effects of banning the use of mobiles on such academic results.

In contrast to Beland and Murphy (2016), our study looks at differences between regions rather than differences across schools and students. So, our paper serves as one more piece of evidence from a macro perspective, rather than a micro one. Besides, to the best of our knowledge, this is the first time that an empirical study sheds light on the effects of mobile phone bans not only on test scores, but also on bullying. Further, we are able to check the bullying effects in four different age groups: 6-to-8, 9-to-11, 12-to-14 and 15-to-17. Hence, our analysis will allow us to identify the age group where banning mobiles has the greatest effect. This is an important contribution of our study since most of the research in this field have been done at the university level and only for academic performance.[10]

To anticipate our results, we find that, during the less than three years that the mobile ban was in force from 2015 to 2017, bullying incidence fell by around 12% to 18% over its pre-intervention levels among 12-to-14 year old kids and 15-to-17 year old adolescents. Also, for the Galicia region, we find that students' scores improved by around 10 points in maths and 12 points in sciences (around 0.55σ and 0.75σ, respectively, of the whole regions-years sample) as compared to a synthetic Galicia that had followed exactly the same trend in these scores before the intervention. Thus, our paper is highly suggestive of the potential beneficial effects of a 'cheap' policy such as banning the use of mobiles at schools.

The rest of the paper is organized as follows. Section 2 provides a description of the data and variables analyzed. Section 3 presents our empirical strategy and methods used. Section 4 reports and discusses the results, and finally, Section 5 concludes.

2 Institutional framework and data

Spain is administratively organised in 17 regions (Comunidades Autónomas). The regional governments are autonomous, among other aspects, to decide upon the regulation and administration of education in all its extension, levels and grades. On this base, two Spanish

[10]As pointed out by Lepp et al. (2014), given that cell phone use is increasingly common in high school and primary education more research need to be done at these education stages.

regional governments (Castilla La Mancha, - CLM henceforth-, and Galicia) passed laws to ban in all the schools of the region the use of mobiles by school students as of 2015.[11] In the rest of regions, the use of mobiles is unregulated, in most of the cases allowing each school to decide upon the use of mobile phones.[12] Thus, results in this paper represent a lower bound to the effects of removing mobiles from schools, since some schools might have decided to ban mobiles at the individual level. The evaluation of impacts conducted in this paper should then be understood as corresponding to a policy of "banning mobile use at schools" as compared to "leaving schools free to decide" upon the matter.

To conduct the analysis, we create a region-level panel using official sources of data for all the 17-Spanish regions before and after the mobile-ban, with the exceptions that we comment next. We set the year 2015 as the first year where the intervention could have had an effect in our outcome variables. For the analysis of bullying, we use information provided by the Spanish Ministry of Education in 2018 about officially reported cases of school bullying from 2012 to 2017.[13] The regions of Cataluña and País Vasco did not report this information and, for this reason, these two regions are not included in our analysis of bullying. The cases were reported separately for four age intervals, namely, school students aged 6-to-8, 9-to-11, 12-to-14, and 15-to-17 year old. For each of these age intervals we construct the number of cases for every 10,000 school students of that age.

For the analysis of academic outcomes, we use the scores obtained by Spanish school students in the PISA assessments from 2006 to 2018. We use in total five PISA assessments, corresponding to years 2006, 2009, 2012, 2015 and 2018. We attribute the scoring of every PISA assessment to the academic achievement of students developed up to the previous year. For instance, the results of PISA-2018 are considered to measure the academic achievement and competencies acquired by students up to year 2017 (included). In accordance to this, we lag the PISA scores of a given call one year. After this, we construct a yearly time series of PISA scores interpolating the scores from one PISA wave to the next, under the assumption that the improvement or the decline in academic competencies evaluated by PISA has occurred gradually between each pair of consecutive assessments. We finally use in the analysis the series of scores spanning from 2006 to 2017.

In the case of the academic outcomes, the regions of Cataluña and País Vasco are included in the analysis. In addition, and unfortunately, the CLM region did not participate in two out of the five PISA calls (2006, and 2012), so that the series of academic results constructed

[11]Castilla La Mancha, Law 5/2014 of 9th October 2014; Galicia, Decree 17, 2015/1/27 of 8th January 2015)

[12]For a summary of schools' practices as regards the use of mobiles in Spanish regions, see *https://www.abc.es/familia/educacion/abci-regula-movil-colegios-cada-comunidad-autonoma-202001131534_noticia.html*, last accessed 20 October 2020.

[13]The data was requested in 2018 from the Spanish Ministry of Education to the Spanish national and local police forces to respond a specific query about this social problem made in the parliament.

[13]INE, *Cifras de población y censos detallados.*

for this region presents limitations when it comes to track their temporal evolution; thus, we will take with special caution the analysis of academic results in the case of the CLM region.[14]

Finally, we construct three additional covariates (/predictors) to be used in the diff-in-diff and SCM estimations. A first variable is the percentage of kids over 10 year old who have mobile.[15] This variable aims at capturing the extent to which the use of mobiles, in or out of schools, is generalised among the kids of a region and year. Second, we construct series of real public spending on education in the elementary and secondary stages of education per school-student[16]. This variable tries to capture changes in the bullying and academic results that might respond to differences in the regional level of investments in education. Finally, we also construct series of real per capita households' disposable income for each region-year.[17] Nominal variables are deflated using CPI indexes at the regional-year level.

Figures 1 and 2 display the sample distribution across regions of the outcome variables before and after the mobile-ban. Figure 1 shows, on the left, the statistics for kids who do not use mobiles yet (aged 6-8), and, on the right, those corresponding to kids and adolescents who are mobile users (aged 9-17). We observe that the number of bullying cases increase appreciable after 2015 among small kids, who are not mobile users yet. The underlying reasons for school bullying at these ages are unknown to us, but this observation suggest that younger children can be viewed as controls in the treatment under study here. However, the officially reported cases of bullying among mobile users remained quite stable over the period of analysis; if anything, they slightly increased (vertical lines indicating the sample averages). Both, Galicia and CML overpassed by more the average line before 2015 than after that year; the region of Galicia improved (reduced) its position in the ranking after the mobile ban.

Finally, Figure 2 shows the PISA scores obtained by Spanish students (aged 15 year old) both in maths and in sciences before and after the mobile ban in 2015. The results in maths have remained quite stable on average, while in science the average Spanish score diminished by around 5 points (average scores changed from 488.6 to 487.2 in maths, and from 494.7 to 489.8 in sciences, before and after year 2015 respectively). Comparing the pre- and post-ban ranking positions of the treated regions, Galicia moved up 3 positions in the ranking in maths and 4 positions in sciences, while CLM moved up 1 position in maths and 2 positions in sciences.

At this descriptive level, however, we cannot discern to what extent the observed changes can be attributed to the mobile ban; differences in (out of school) mobile use among kids

[14]The participation of students in the PISA calls is not compulsory but decided by each government. In Spain, each regional government decides on the participation of their students.

[15]INE, *Encuesta sobre equipamiento y uso de tecnologías de información y comunicación en los hogares.*

[16]INE, *Estadística de gasto público en educación*, EDUCAbase

[17]INE, *Contabilidad regional de los hogares*

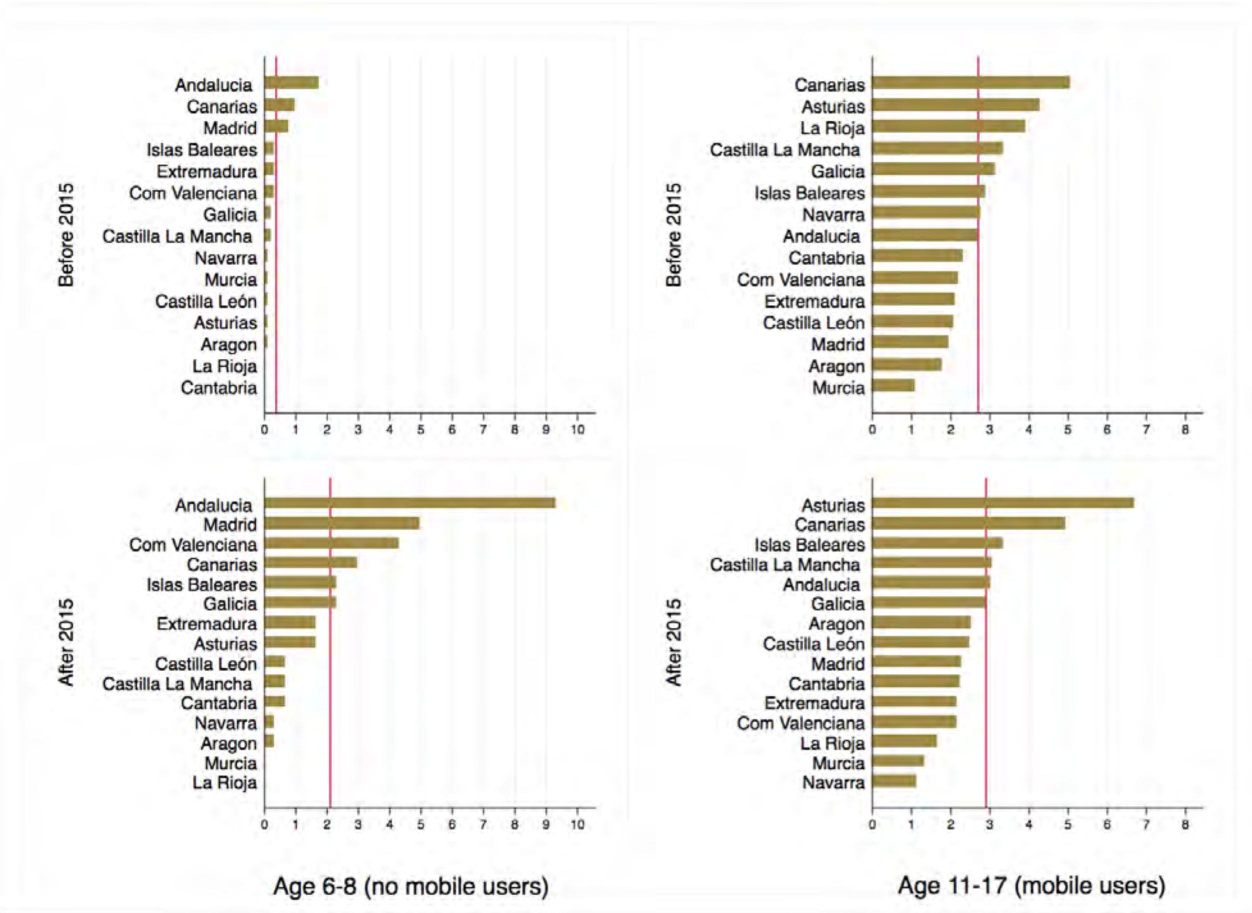

Figure 1 : Cases of bullying per 10,000 individuals in each age-interval.

Own elaboration. *Source:* Spanish Ministry of Education, 2018 (bullying cases) and INE (population by age, region, and year).

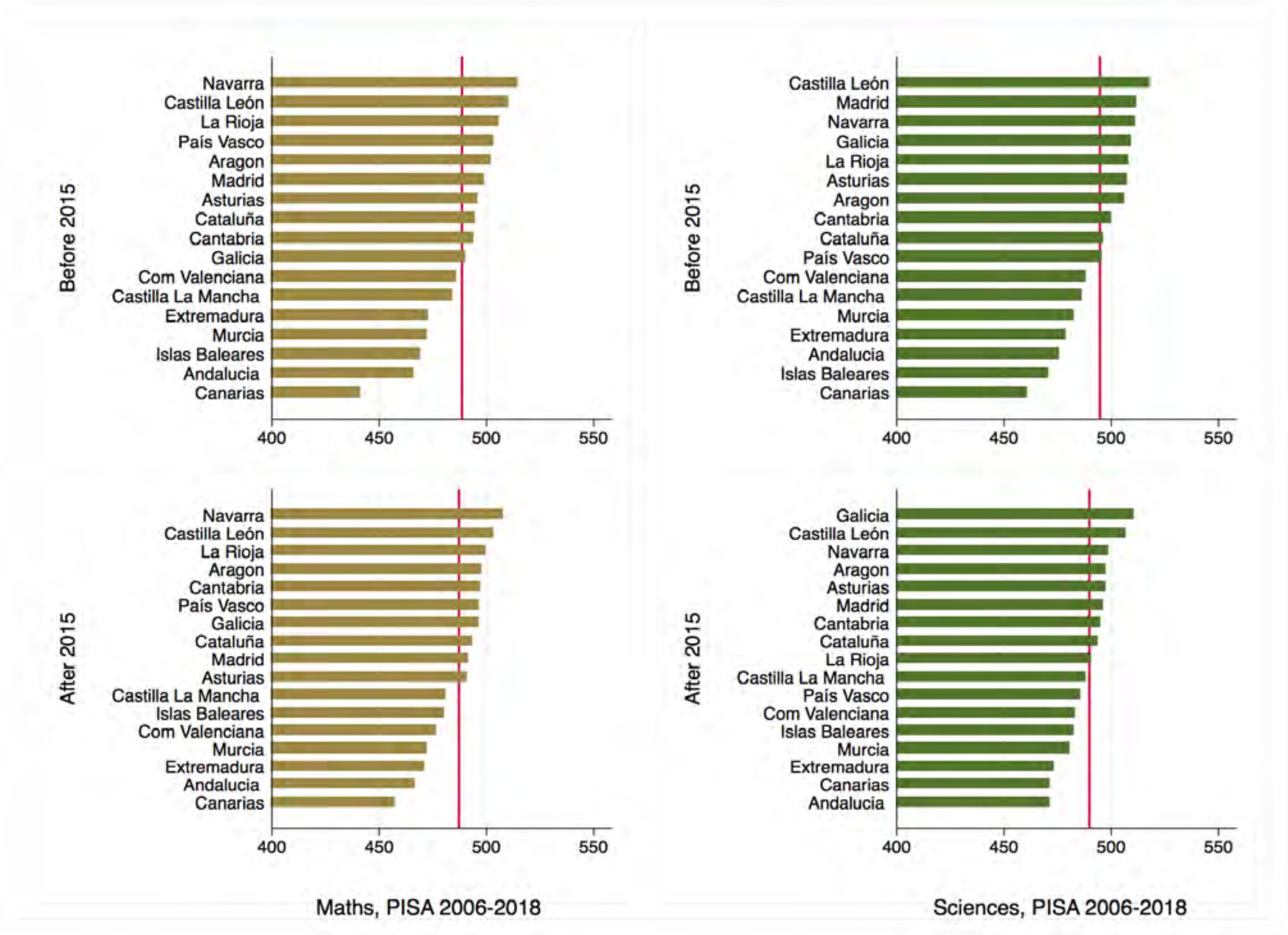

Figure 2 : PISA Assessments in maths and sciences. 2006-2018.

Notes: PISA scores in each wave (every 3-years) are attributed to competencies acquired by students up to the previous year, and values are interpolated between 2 consecutive waves.

across regions and over time, in income levels, or in educational expenditures, for instance, are not controlled for in the figures. In the next section we describe the empirical strategy that we follow to identify the impact of the mobile ban, and then we present the obtained results.

3 Methods

We estimate the impact of the mobile phone ban exploiting differences between the treated region and the rest of regions in Spain before and after the mobile ban. In the case of the bullying data, we conduct difference-in-differences estimation separately to the four age intervals (6-8, 9-11, 12-14 and 15-17 year olds) and for each of the treated regions, Galicia and CLM. Available data in this case cover the period 2012-2017. For the analysis of academic outcomes, we apply diff-in-diff regression to both the Galicia and the CLM cases, and the Synthetic Control Method (SCM henceforth, Abadie and Gardeázabal, 2003; Abadie et al., 2010) to the case of the Galicia region, for which we count on a more complete time series of observations (PISA assessments' scores of the region in maths and sciences from 2006 to 2017).

3.1 Impacts on Bullying: diff-in-diff analysis.

Our diff-in-diff regression equation can be written as follows:

$$Y_{it} = \alpha + \beta_0 \; pre_{t-1} \times D_i + \beta_1 Post_t \times D_i + \gamma \mathbf{x}_{it} + \delta_i + \tau_t + u_{it} \tag{1}$$

where subscripts i and t denote the region and year, respectively. The dependent variable, Y_{it}, is the number of cases of bullying officially reported by region i in year t to the Spanish Ministry of Education. $Post_t$ is a dummy-step variable taking on value 1 for the year of implementation and subsequent years (2015-2017); D_i is a dummy variable for the treated region, capturing time-constant differences between it and the rest of regions, if any. The term $pre_{t-1} \times D_i$ is included in equation (1) to test for the assumption of parallel trends prior to the ban, and it is the product of a dummy variable taking on the value 1 for year 2014 times the dummy accounting for the treated region. This term has to be null (estimate of β_0 not significantly different from zero) for the DID estimation to be a valid identification strategy; that is, prior to the treatment there must be no differences in trends between the treated and the control regions. In addition, $\mathbf{x}_{it}$ stands for a vector of other covariates entering the estimation equation. The variables included into vector $\mathbf{x}_{it}$ are the percentage of mobile usage by kids in the region-year, real public spending on education in elementary and secondary education, and region-year per capital real disposable income. Finally, δ_i stand for region-fixed effects (thus, absorbing time-constant differences between the treated region and the rest of regions),τ_t is a full set of year dummies, and u_{it} stands for the *iid* error of the model.

In equation (1), once region-level specific differences, common year effects, and other region-year differences in covariates have been controlled for, parameter β_1 identifies the treatment effect. The equation is estimated for Galicia and for CML separately, and in both cases, we estimate the model for 4 age intervals: 6-8, 9-11, 12-14, and 15-17 year old school students.

3.2 Impacts on Academic performance

3.2.1 Diff-in-diff analysis

The analysis of the impact of the mobile ban on academic performance is twofold. First, we apply diff-in-diff estimation to an equation like (1). The time period spans now from year 2006 to year 2017. In this case, the term $pre_{t-1} \times D_i$ is the product of a dummy variable taking on the value 1 for years 2012-to-2014 times the dummy accounting for the treated region. As above mentioned, if significant, this term would be indicating that the observed differences post-ban could in fact have been initiated prior to the intervention, thus invalidating the diff-in-diff identification of the treatment effect.

Equation (1) is estimated for Galicia and for CML separately, and, in both cases, we apply the model separately to the PISA scores in maths and in (natural) sciences obtained by the Spanish 15-year old students in each region. Unfortunately, the available data for CLM does not allow us to trace out a fully reliable series of PISA assessments, since students of this region did not participate in the PISA calls of years 2006 and 2012. This compels us to interpolate the data between years 2009 and 2015 for the CML region, jumping over year 2012, which, on the contrary, is available for Galicia and the rest of regions. This prevents us from making a reliable pre-trend analysis for the CML case. Thus, although we run our diff-in-diff regression for this region, we take with caution the obtained results in this case.

3.2.2 Synthetic Control Method

To further shed light on the impact that the mobile ban might have had on academic outcomes, we use the data series of PISA assessments for Galicia to apply a SCM estimation (Abadie and Gardeazábal, 2003, and Abadie, et al., 2010). One of the advantages of the SCM for comparative case analysis over standard diff-in-diff regression is that it solves the arbitrariness in the choice of the control units. Instead, the SCM conducts a formalized data-driven procedure that constructs a weighted combination of a small number of unaffected units, taken from the set of potential controls, or donor pool, as the most appropriate unit of comparison.[18]

[18]For a discussion of the data requirements and advantages of the SCM see Abadie (2020).

In the SCM, the counterfactual outcome Y_{it}^N is estimated as the outcome corresponding to that synthetic unit. More formally, considering $(J+1)$ regions, with $(J=1)$ being the treated one, the synthetic control is constructed from a $(J \times 1)$ vector of weights, $\mathbf{W} = (w_2, ..., w_{J+1})'$ that allows us to define the estimators for Y_{it}^N and for the effect on the treated unit τ_{1t} as follows:

$$\hat{Y}_{jt}^N = \sum_{j=2}^{J+1} w_{jt} Y_{jt} \tag{2}$$

$$\hat{\tau}_{1t} = \hat{Y}_{jt}^N - \sum_{j=2}^{J+1} w_{jt} Y_{jt} \tag{3}$$

where the weights are restricted to be non-negative and to sum to one.

In addition, to apply the SCM we need a set of k potential predictors of the outcome trends. As such predictors, we use past values of the own outcome of interest plus the covariates defined above (percentage of kids using mobiles, public spending on education, and disposable real income per capita). The method uses a weighting-matrix, $\mathbf{V}$, that contains the relative importance of each of the k predictors in constructing the synthetic control. The main challenge of the method is how to find the optimal weighting matrices $\mathbf{W}$ and $\mathbf{V}$. We follow Abadie et al. (2010), who propose choosing the $\mathbf{V}$ that minimizes the root mean squared prediction error (RMSPE) of the pre-intervention outcome between the treated unit and the control unit. Then, $\mathbf{W}$, which is a function of $\mathbf{V}$, is picked to minimize the RMSPE of the predictor variables for a given $\mathbf{V}$.

Below, after the SCM estimation and to evaluate the significance of our estimates, we report standardized p-values constructed from the distribution of placebo or permutation tests following Abadie et al. (2010). This is done by estimating the same model on each untreated unit with the same intervention years and period and removing the actual treated unit from the potential donor pool of these other units. These are nonparametric exact tests, which have the advantage of not imposing any distribution on the errors. If the effect of the intervention on the treated unit is significant (not observed by chance), we should observe that the probability of finding comparable estimated effects in other units is very low (see, e.g. Galiani and Quistorff, 2017, for further details).

3.3 Results

3.4 Impacts on bullying

Table 1 displays the estimated impacts of the mobile ban on officially reported cases of bullying. For both treated regions, Galicia and CML, we show the impacts by age interval. A first result to notice is that for the 6-8 year old interval we find no significant (and positive) treatment effects in neither region. These two diff-in-diff regressions can be taken as falsification checks, to the extent that they show that the mobile ban had no effect on the age group who is not mobile user. For school students aged 12-14 and 15-17 the picture is different. In these cases, and both taking as case study either Galicia or CLM, the results point to a reduction in bullying after the mobile ban. Taking into account the pre-ban average values of bullying in each age interval, the estimated impacts would account for significant reductions of around 12.5% to 18% of the pre-intervention cases of bullying, depending on the case.

In the case of Galicia, negative and significant effects are also found for the 9-11 year old interval, although no significant effects are found on this age interval for the CML case. Since this is an age interval where the use of mobiles has already started but is still moderate (around 25 to 30 % according to official data), both results can be accepted as possible.

In all the three older age intervals, the pre-trend effect is not statistically significant, not even of the same sign that the treatment estimated effect. Thus, the estimated treatment effects can not be attributed to different trends between the treated and the control regions already initiated prior to the treatment. The parallel trends assumption, crucial for validity of the diff-in-diff analysis, is then supported by our data.

In the bottom part of Table 1 we display the results of a series of placebo checks that we also perform with the bullying data. We estimate the same model on each untreated unit (13 regions) with the same intervention years and periods and removing the actual treated unit from the control group. In the table we report the number of regions other than the treated region for which we estimate a negative and significant treatment effect without evidence of no-parallel trends (no significant estimates for the term $pre_{t-1} \times D_i$). Only in 1 out of the 13 cases we obtain a negative and significant effect post-intervention. Then, this would point to a probability of 0.076 of finding by change a comparable result. In addition, the region that turns out to show a significant effect is a different one in each of the age intervals, that is, no region other than the treated ones show significant effects in, at least, two of the age intervals considered. This suggests that the by-chance findings are more the ones in the placebo analysis that the estimated effects for Galicia and CLM.

Table 1 : Bullying. Diff-in-diff analysis. Years 2012-2017

Dep.variable: Officially reported cases per 10,000 individuals (by age interval, region and year)
Source: Spanish Ministry of Education

	Treated region: Galicia				Treated region: CLM			
	(1a) age 6-8	(2a) age 9-11	(3a) age 12-14	(4a) age 15-17	(1b) age 6-8	(2b) age 9-11	(3b) age 12-14	(4b) age 15-17
Treated region	-0.107	0.335	0.666**	1.947***	-0.494	0.135	2.434	2.362***
	(0.360)	(0.415)	(0.286)	(0.245)	(0.567)	(0.707)	(2.683)	(0.545)
Pre×treated[a]	-0.175*	-0.075	0.386	0.293	0.325**	0.129	0.103	-0.427
	(0.087)	(0.167)	(0.314)	(0.303)	(0.121)	(0.242)	(0.649)	(0.306)
Post×treated[b]	0.072	-0.466***	-0.522**	-0.700***	0.012	0.218	-1.062**	-0.514**
	(0.066)	(0.121)	(0.234)	(0.178)	(0.084)	(0.168)	(0.425)	(0.203)
Mobile users (%)	0.004	0.003	-0.067**	-0.068	0.006	0.005	0.013	0.032
	(0.008)	(0.018)	(0.031)	(0.046)	(0.008)	(0.018)	(0.036)	(0.021)
Educ pub spend.	-0.030	-0.095	-0.316	0.013	-0.045	-0.114	-0.415	-0.016
	(0.104)	(0.165)	(0.256)	(0.284)	(0.097)	(0.171)	(0.364)	(0.231)
Income	-0.679	0.587	-2.657**	-2.428**	-0.793	0.487	0.836	2.194
	(1.373)	(1.492)	(1.077)	(0.918)	(1.397)	(1.508)	(6.546)	(1.297)
Constant	0.221	0.137	3.506***	3.297***	0.243	0.137	2.432	2.230***
	(0.477)	(0.498)	(0.326)	(0.254)	(0.478)	(0.511)	(1.907)	(0.653)
Year effects	yes	yes	yes	yes	yes	yes	yes	yes
Region effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	84	84	84	84	84	84	84	84
N. Regions	14	14	14	14	14	14	14	14
Placebos[c]		1	1	1		1	1	1
R-squared	0.461	0.460	0.526	0.154	0.483	0.422	0.717	0.344
Pre-treatm avg (treated region)	0.099	0.564	4.432	4.485	0.097	0.466	5.812	3.87

Robust clustered (by region) standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. [a] Pre×treated: treated region in the year previous to the treatment (year 2014); if significant, it indicates non parallel pre-trends. Post×treated: treated region in years after the treatment (years 2015 to 2017). All the regressions are weighted by the population of each region, year and age-interval. Quantitative co-variates are centered with respect to the annual mean of the variable. The regions of Cataluña and País Vasco are not included since they did not report the data of bullying cases. The regions with significant effects in the placebo checkings are La Rioja, Com. Valenciana, and Murcia, for the 9-11, 12-14, and 15-17 age intervals respectively.

3.5 Impacts on Academic performance

Tables 2 and 3 display the estimation results for the impacts of the mobile ban on the academic results obtained by Spanish 15-year old students in the PISA assessments undertaken from 2006 to 2018. We focus on the scores obtained by the students on maths and sciences (there are no available results for the 2018 results of the reading tests). As mentioned above, we take with caution the results obtained for the CML region since students of this region did not participate in the PISA calls of years 2006 and 2012. This prevents us from making a reliable pre-trend analysis for the CML region, since the data has been linearly interpolated between years 2009 and 2015, and extrapolated from 2009 to 2006.

In columns (1a) and (1b) of Tables 2 and 3 we display the diff-in-diff results before other covariates are included, whereas in columns (2a) and (2b) we discount the effects of such covariates, namely, the share of kids who have a mobile in the region-year, educational public spending, and real disposable per capita income of the region-year. A first observation in Table 2 is that there is no evidence of pre-treatment differences in the PISA scores. That is, prior to the mobile ban, the Galicia region did not display any significant difference in their students' results in the PISA assessments with respect to the rest of regions in Spain. However, after the mobile ban, the academic results in maths increased by more than 9 points in maths, and by more than 7 points in sciences. These are improvements of around 0.5 times the standard deviation of the scores for all regions-years prior to the treatment, and more than 4 times and 3 times, respectively, the standard deviation of this region' results from 2006 to 2015.

The comparison of columns (1a) and (2a) shows that part of the post-ban increases, both in maths and in sciences, can be attributed to changes across regions and/or over time in the use of mobiles by kids. In particular, the results suggest that, beyond their use inside schools, a higher percentage of kids using mobiles is negatively associated to their academic results. This result would be pointing towards a negative impact of mobile use on academic results, which have implications for further advances on academic achievement given the rising worldwide trends in such use by youngsters. On the other hand, our results point out to a positive impact of educational public spending on the academic performance of students in the PISA assessments on maths, although no significant effects are found of this variable in the case of sciences. No significant effects are found for the region-year levels of per capita real disposable income.

Table 3 displays the diff-in-diff results for the CLM region. The estimated effects of the mobile ban in this case are inconclusive. On the one hand, we estimate positive post-ban effects in both maths and sciences although no statistically significant in maths and no different from the prior pre-trend estimated effect in sciences. Thus, the estimated results would be suggesting no improvement in academic results from 2025 to 2018; however, since PISA results for 2012 are not available for this region, we can not compare this change with

Table 2 : PISA. Diff-in-diff analysis. Years 2007-2017

	Treated region: Galicia			
	(1a) Maths	(2a) Maths	(1b) Sciences	(2b) Sciences
Treated region	-9.045***	-0.302	3.324	-0.725
	(1.623)	(7.037)	(4.162)	(9.360)
Pre×treated[a]	1.548	0.859	0.212	3.706
	(1.545)	(2.361)	(1.357)	(3.542)
Post×treated[b]	9.236***	6.371**	7.059***	8.395*
	(2.144)	(2.657)	(2.236)	(4.294)
Mobile users (%)		-0.277**		-0.431**
		(0.114)		(0.150)
Educ pub spend		2.982**		-0.971
		(1.129)		(2.804)
Income		31.589		-11.493
		(21.754)		(31.598)
Constant	497.8***	487.8***	501.4***	502.1***
	(2.626)	(9.705)	(3.815)	(12.054)
Year effects	yes	yes	yes	yes
Region effects	yes	yes	yes	yes
Observations	192	192	192	192
N Regions	16	16	16	16
R-squared	0.927	0.938	0.887	0.903
Pre-treatment avg (treated region)	491	491	509	509

Robust clustered (by region) standard errors in parentheses. * $p<0.10$ ** $p<0.05$ *** $p<0.01$. [a] Pre×treated: treated region in the latest years previous to the treatment (years 2012, 2013, 2014); if significant, it indicates non parallel pre-trends. Post×treated: treated region in years after the treatment (years 2015 to 2017). All the regressions are weighted by the population of each region, year and age-interval. Quantitative co-variates are centered with respect to the annual mean of the variable.

the change that 2012 could have represented with respect to 2009 and prior results as we did with the rest of regions. Also, the results from 2006 to 2009 have been extrapolated, without available information for 2006.

Next, in Table 4 and Figure 3 we display the results for the SCM applied to the Galicia region. As already mentioned, the SCM provides a systematic data-driven procedure to create the (weighted) combination of regions that best resembles the actual Galicia before the implementation of the mobile ban. The SCM constructs the synthetic Galicia for PISA results on maths as a combination of Navarra (41.2%), Canarias (21.6%), La Rioja (14.4%), Extremadura (12.8%), and Cataluña (10.0%); for the PISA results in sciences, it is a combination of Castilla-León (79.0%), Islas Baleares (17.0%) Cataluña (3.0%), and Madrid (1%). All the other regions in the donor pool were assigned zero weights. The SCM estimation ex-

Table 3 : PISA. Diff-in-diff analysis. Years 2007-2017

	Treated region: Castilla-LM			
	(1a) Maths	(2a) Maths	(1b) Sciences	(2b) Sciences
Treated region	-18.218***	-6.760	-11.045***	2.785
	(0.836)	(13.667)	(0.778)	(11.738)
Pre×treated[a]	0.790	5.024***	8.047***	10.952***
	(1.525)	(1.291)	(1.352)	(1.176)
Post×treated[b]	-0.214	1.983	10.214***	11.623***
	(2.137)	(1.984)	(2.241)	(2.075)
Mobile users (%)		-0.297**		-0.208
		(0.130)		(0.143)
Educ pub spend		2.774**		0.770
		(1.134)		(0.800)
Income		26.122		32.760
		(29.522)		(24.661)
Constant	500.8***	490.7***	490.1***	476.0***
	(1.902)	(13.943)	(1.199)	(11.941)
Year effects	yes	yes	yes	yes
Region effects	yes	yes	yes	yes
Observations	192	192	192	192
N Regions	16	16	16	16
R-squared	0.929	0.938	0.908	0.914
Pre-treatment avg (treated region)	483	483	481	481

Robust clustered (by region) standard errors in parentheses. * p<0.10 ** p<0.05 *** p<0.01. [a] Pre×treated: treated region in the latest years previous to the treatment (years 2012, 2013, 2014); if significant, it indicates non parallel pre-trends. Post×treated: treated region in years after the treatment (years 2015 to 2017). All the regressions are weighted by the population of each region, year and age-interval. Quantitative co-variates are centered with respect to the annual mean of the variable.

hibits then sparcity in the choice of regions to construct the counterfactual (Abadie, 2020), and also, as can be seen in the bottom part of Table 4, a close match between the pre- and post-intervention values of the predictors and low pre-intervention prediction error (root of the mean square prediction error, RMSPE, of around 0.4 for outcome variables that have average values of around 490).

Figure 3 permits us to visualise the almost perfect fit between the treated unit (Galicia) and its synthetic counterpart in the pre-intervention period. However, after the ban, the Galicia region seems to have escaped from the decline that the PISA results exhibited in the synthetic Galicia. The estimated effects are of an order of magnitud of around 10.7 and 12.7 points on maths and sciences, respectively, as of 2017 (when the outcome takes the value of the PISA assessment of 2018). Under our assumption that the academic achievements have transited smoothly from the previous PISA results (year 2015), the average estimated effects over the post-intervention period are of around 7.01 and 8.2 for maths and sciences,

Table 4 : PISA. Synthetic Control Method for Galicia region.

	Years 2007-2017	
Estimated Treatment effects:		
	MATHS	SCIENCES
lead 0 (year 2015)	2.963***	3.429***
lead 1 (year 2016)	7.404***	8.574***
lead 2 (year 2017)	10.676***	12.731***
Donor Regions:		
	Navarra (41.2%)	Castilla-León (79.0%)
	Canarias (21.6%)	Islas Baleares (17.0%)
	La Rioja (14.4%)	Cataluña (3.0%)
	Extremadura (12.8%)	Madrid (1.0%)
	Cataluña (10.0%)	
Predictors' values:		
	Treated / Synthetic	Treated / Synthetic
PISA 2006-2008	490.0 / 489.9	505.6 / 505.7
PISA 2008-2010	488.3 / 488.4	508.0 / 508.1
PISA 2010-2012	489.7 / 489.8	511.3 / 511.5
PISA 2012-2015	493.0 / 492.5	511.7 / 511.3
Mobiles	65.91 / 65.86	65.91 / 64.30
Educ pub spend (log)	-8.50 / -7.17	-8.51 / -8.35
Income	9.25 / 9.36	9.25 / 9.34
RMSPE	0.409	0.411
PISA Pre-2015 mean	489	495
N. potential donors	16	16

Each lead corresponds to the number of years after the intervention. *** standardized p-values < 0.01 (see Abadie et al. 2010). They reveal that no other region in the donor pool exhibits such large estimated effects in the placebo checks.

respectively. The estimated effects with the SCM are thus quite comparable to the diff-in-diff results displayed in 2, and they account for around one half of the standard deviation of the PISA assessments across all regions and years of the period of analysis (18.4 and 15.9 for maths and sciences, respectively). Finally, the p-values derived from the placebo tests in the SCM analysis indicate that for no other region the SCM finds comparable results to the ones obtained for the treated region.

4 Conclusions

In this paper, we have studied the effects that banning the use of mobiles in schools may have on bullying and academic achievement. Using as comparative case studies two regions in Spain whose autonomous governments established mobile bans as of year 2015, we have applied diff-in-diff regression and the synthetic control method to analyse reported cases of

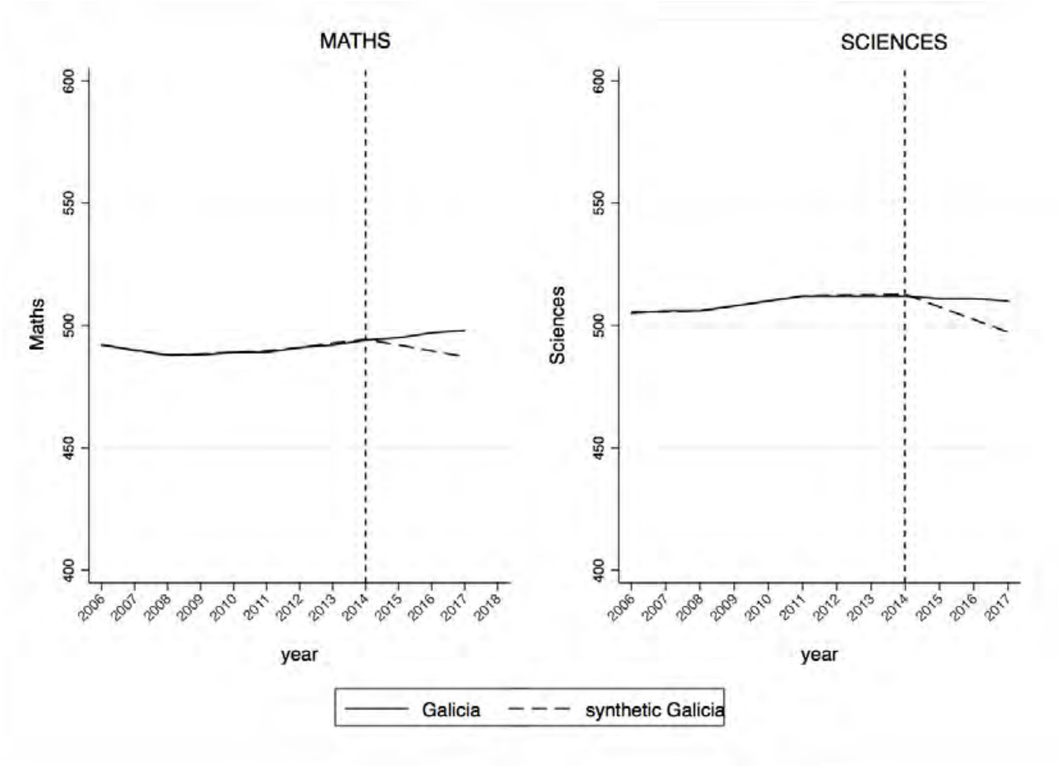

Figure 3 : SYNTHETIC CONTROL METHOD RESULTS FOR PISA ASSESSMENTS IN MATHS AND SCIENCES IN THE REGION OF GALICIA. 2006-2017.

Notes: PISA scores in each wave (every 3-years) are attributed to competencies acquired by students up to the previous year, and values are interpolated between 2 consecutive waves.

bullying and PISA scores in maths and sciences. We find that, during the less than three years that the mobile ban was in force from 2015 to 2017, bullying incidence fell by around 12% to 18% over its pre-intervention levels among 12-to-14 year old kids and 15-to-17 year old adolescents. Also, for the Galicia region, we find that students' scores improved by around 10 points in maths and 12 points in sciences (around 0.55σ and 0.75σ, respectively, in the whole regions-years sample) as compared to a synthetic Galicia that had followed exactly the same trend in these scores before the intervention.

The evaluation of impacts conducted in this paper should be understood as corresponding to a policy of "banning mobile use at schools" as compared to "leaving schools free to decide" upon the matter. Thus, our results have to be taken as a lower bound to the potential effects of banning (or at least regulating) the use of mobiles at schools, and they are highly suggestive of the potential beneficial effects of such a 'cheap' policy.

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