Information Shocks and Internet Silos: Evidence from Creationist Friendly Curriculum*

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ABSTRACT

How the Internet affects the ability of its users to seek out information which either supports or contradicts their existing beliefs remains an open question. On the one hand, the Internet should be able to supply information which might correct falsifiable beliefs. On the other hand, as users control the manner of their search, they may find sources which support their beliefs, even if those beliefs go against the mainstream consensus. To examine this, we analyze the effect of the Louisiana Science Education Act (2008), which allowed the teaching of creationism as an alternative 'theory' to evolution in Louisiana schools, on students' science test scores in nationally administered tests. Using detailed data on Louisiana schools, we employ a difference-in-differences strategy to document that science test scores declined after the law relative to schools in neighboring Texas. After the change in policy, Louisiana students were more likely to seek out information on the Internet using search terms which led them to web pages that reinforced a creationist message. The effect of the law was primarily driven by regions with high Internet penetration and low parental education levels.

Keywords: Evolution, Creationism, Internet, Test Scores, Louisiana Science Education Act

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1. Introduction

Despite the advent of the Internet and the proliferation of content online, it remains unclear how Internet users draw on sources which might provide facts to either support or challenge their existing beliefs. Do such sources help web users to correct inaccurate beliefs, or reinforce their prior, possibly flawed, beliefs (Sunstein (2001), Sunstein (2007) Gentzkow and Shapiro (2011), Boxell et al. (2017)?

To explore this question, we use a shift in the 'facts' people were exposed to. In June 2008, the Louisiana legislature passed the 'Science Education Act,' which allowed teachers in public schools to use 'supplemental materials' in science class while covering topics such as evolution and global warming.[1] This policy has been criticized by scientists and educators, including Nobel laureates, who suggest that it implicitly allowed religious beliefs such as creationism to be taught alongside scientific theories of evolution in the classroom. There have been several unsuccessful attempts to repeal this law, which is said to hamper the spread of scientific knowledge. Proponents of the law argue that allowing the teaching of creationism enhances critical thinking. There is anecdotal evidence that creationism is being taught in Louisiana schools.[2]

The Internet gives students greater access to information in general. However, it is not clear whether students use this resource to contradict and correct beliefs conveyed in the classroom setting (Cantoni et al., 2017), or to reinforce those beliefs. Therefore it is unclear whether instructional content going against the existing scientific consensus would have any effect.[3]

In this paper, we ask how an information shock - in terms of content supporting different beliefs taught in school - affects student knowledge and performance. We also ask

[1] Even though the law implicitly allowed the use of additional teaching materials to challenge other phenomena backed by scientific evidence such as global warming, critics mainly saw it as a tool to introduce the teaching of creationism in science classrooms. See http://www.nola.com/education/index.ssf/2017/03/science_evolution_standards.html for more on this.

[2] See http://www.slate.com/articles/health_and_science/science/2015/04/creationism_in_louisiana_public_school_science_classes_school_boards_and.html for anecdotal evidence. See http://www.salon.com/2015/06/11/its_official_louisiana_public_schools_are_using_the_book_of_genesis_in_high_school_science_classes/, which discusses how the Book of Genesis is being used in at least one school district's science classes. http://www.bjupress.com/resources/science/grade-5/ is a typical text book which emphasizes God's role - 'Science 5 focuses on man's use of God's creation and design as well as a study of minerals and rocks, fossils, matter and heat, sound and light, weather, biomes, ecosystems, and the respiratory and circulatory systems.'

[3] Edmond (2013) models sophisticated consumers of potentially biased media and shows how media centralization can help governments control the flow of information.

whether access to the Internet affects how students use this information, and whether receiving content supporting creationism subsequently affects their performance on science tests. To answer these questions, we analyze the effect of the Louisiana Science Education Act on student performance in high school science tests as part of the nationally administered American College Testing (ACT) standardized tests. We use school-level ACT science test score data between 2003 and 2013 to see whether the policy had any effect on student performance. Additionally, using Federal Communications Commission (FCC) data on the number of Internet providers, we assess how the effect of the law on science test scores varied with Internet penetration.[4]

We use a difference-in-differences setup by comparing science test scores in Louisiana schools before and after the law was passed, relative to schools in Texas which did not see any similar policy change over this period. Our identifying assumption is that the trends in science test scores between Louisiana and Texas, that are unexplained by school and time fixed effects, would have remained the same in the absence of the policy being enacted in Louisiana. This is the standard parallel trends assumption. We then explore the heterogeneous effects of this law across regions with different levels of Internet penetration and education.

After the law was enacted, science test scores declined in Louisiana schools relative to those in Texas. Quantitatively, the policy change lead to about half a standard deviation decline in science test scores. This magnitude is similar to those documented by Belo et al. (2013), who find a negative effect of Internet use on middle school student test scores in Portugal.

This effect is primarily driven by schools located in relatively underprivileged areas, that is, those with low levels of parental or family education. Moreover, it is schools in underprivileged areas with high Internet penetration which drive our results.

By carrying out a series of placebo checks, we rule out obvious alternative channels which could explain the change in test scores around the time the law was passed. First, we do not find any similar decline in math test scores after the law passed. This rules out a general decline in student performance in analytical subjects such as science and math

[4] We use the number of Internet service providers (ISPs) as a proxy for Internet adoption. There is a large amount of evidence, which we document in Section 3.2, showing that the number of ISPs is highly positively correlated with Internet adoption and usage. In this sense, we can use Internet penetration and Internet adoption interchangeably.

around the same time. Second, to rule out a general downward trend in science test scores, we assign fake policy dates while analyzing data from the pre-policy years. We do not find any statistically significant effect when the policy date is falsely assigned to any of the pre-policy years. Last, there is no discontinuous change in other observables related to school education revenues or expenditures, especially associated with science instruction in the classroom. Overall, results in all the placebo specifications are consistent with our identifying assumption, i.e., the parallel trend assumption.

We then investigate the mechanism. The decline of science scores in high-penetration areas suggests that information sought out online reinforces the creationist teachings in schools, consistent with the echo chamber hypothesis (Sunstein (2001), Sunstein (2007), Van Alstyne and Brynjolfsson (2005), Halberstam and Knight (2016)). In line with this, we find that there was an increase in Google search intensity of keywords related to creationism in Louisiana relative to Texas after the law was introduced. There was a significant increase in creationism-related online search intensity even when measured relative to evolution-related search terms. Moreover, we show that areas with low levels of adult education and high Internet penetration experience a decline in science test scores but variation in other underlying demographic variables such as population size, population density and commuting times cannot generate the same effect. This seems to capture a phenomenon particular to how people might seek out information online in sync with their existing facts and which cannot be explained by other underlying demographic characteristics.

Our findings contribute to a few related streams of literature. The first literature investigates how the Internet affects educational outcomes. In general, Internet access does not increase test scores. Belo et al. (2013) find that Internet use in Portuguese schools decreased student test scores, mainly because of time away from work on websites such as Youtube. Goolsbee and Guryan (2006) analyze data on California schools to find no effect of Internet subsidies on student performance along different dimensions. Specific technologies, though, may help students. Banerjee et al. (2007) find that computer-aided programs aimed at improving math scores in urban Indian schools lead to better student performance in the short run. Our paper contributes to this literature, which shows heterogeneous effects of the Internet and its potential to simply reinforce information provided in an educational system.

Our results also relate to studies about whether online content leads to ideological segregation or broadened horizons. These studies also have mixed results. Gentzkow and Shapiro (2011) do not find evidence for a substantial level of online segregation in news consumption. Lelkes et al. (2015), on the other hand, find that access to broadband Internet increases political polarization. Our results suggest that the Internet can exacerbate existing levels of misinformation, by students seeking out creationist information online.

We also add to the limited number of studies which attempt to identify the causal effect of school curriculum and educational content on student outcomes. Cantoni et al. (2017) use a textbook reform in China to find that it led students to feel more favorable towards the Chinese government and have greater skepticism about the free market. Clots-Figueras and Masella (2013) analyze a language policy change in the Catalan education system instituted by the Catalan government and demonstrate that students who were exposed to more years of compulsory education in Catalan identified more with being Catalan than Spanish. We add to this literature, by documenting how the use of the Internet can exacerbate the misinformation propagated in the classroom. Analyzing how the Internet affects the way classroom teaching is processed by students is a fundamental issue that Cantoni et al. (2017) notes but leaves entirely unexplored.

The paper proceeds as follows. Section 2 provides institutional details. Section 3 describes the data and while Section 4 lays out our empirical strategy. Section 5 reports the regression results with Section 6 looking at some robustness checks, and Section 7 concludes.

2. Background

2.1. Louisiana Science Education Act

In June 2008, the Science Education Act was passed by the Louisiana State Legislature and was signed into law by Governor Bobby Jindal. The law was aimed at allowing teachers in public schools to question and critique existing scientific theories such as evolution and global warming. In addition, teachers were indirectly allowed to present alternate theories such as creationism. Creationism is a belief that the earth originated through an act of God, rather than a natural process such as evolution. Young Earth creationists believe that the Earth is less than ten thousand years old, whereas scientists believe that the Earth is 4.5 billion years old.

Louisiana was the first state to pass such a law and still remains the only state to have such an education policy in place. Other states, including Texas, have tried and failed to pass similar bills. Since lawmakers in Texas have also attempted to enact such a law several times, Texas seems to serve as the most natural control group relative to Louisiana.[5]

2.2. The American College Testing Assessment (ACT)

The ACT is a standardized test which is taken by high school students in the U.S. in order to apply for college. It is a competitor of the Scholastic Assessment Test (SAT). All four-year college degree-granting institutions accept ACT test scores. In 2011, the ACT overtook the SAT in terms of the number of students taking that test. The ACT consists of tests on four subjects: English, Math, Reading and Science, with each subject being graded on a scale of 1-36.

The science test has 40 multiple choice questions, which need to be answered within 35 minutes. They are mainly related to the analysis of different scientific concepts based on passages provided during the test. While the ACT test requires specific preparation, they still assume that the students will have some knowledge of the material taught in science lessons in school.[6] Advanced knowledge of scientific theories is not required for the test, though given the time crunch, it is evident that prior information about the concepts could give a substantial competitive edge.[7] This view is echoed by Kaplan Test Prep, one of the most widely used test preparations website, which notes that "...you do not have to be an excellent Science student to score highly on the ACT Science test; some knowledge of the concepts tested and a familiarity with the presentation of certain concepts will almost certainly lead to better scores." [8] In Figure 1, we show an example of a typical passage (taken from Kaplan's webpage) which would appear as part of an ACT science test question. The questions would be based on the evolution-related passage. The passage highlights two differing hypotheses of evolution- 'The Multi-Generational Hypothesis' and 'The Out of Africa Hypothesis.' While students could answer questions based solely on the information provided in the passage, without any prior knowledge of these competing hypotheses, it is evident that familiarity

[5] For more information on attempts to introduce similar bills and enact these laws in different states, see https://www.aibs.org/public-policy/evolution_state_news.html.

[6] More details on science test questions can be found here: http://www.act.org/content/act/en/products-and-services/the-act/test-preparation/science-practice-test-questions.html.

[7] For more information on what exactly students need to do for preparing for the ACT science test, see http://blog.prepscholar.com/the-only-actual-science-you-have-to-know-for-act-science.

[8] See Kaplan's webpage for more information https://www.kaptest.com/study/act/the-act-science-test-biology-basics/.

with topic would definitely give them an edge in terms of time and ultimately in test scores. [9] Another example science test passage hosted on Kaplan's website sourced from www.act.org requires analysis of passages related to DNA and genetics - concepts which are central to evolutionary theories (https://www.kaptest.com/study/act/the-act-science-test-biology-basics/). Given this background, it is evident that if science teachers spend a significant amount of time using supplemental materials, it will distract students from core topics like human evolution which appear in the ACT, which would in turn, presumably, affect their performance in the ACT science tests.

The ACT takes place about six times during the year between September and June of the academic year and is available in all U.S. states. Students are free to appear for the test on a date of their choice and can re-take it if they do not feel satisfied with their performance. The timing of the law plays a role in terms of how we define the post-policy period. The law was passed in June 2008 and we define the post-policy period as starting in the 2008-09 academic year, which begins in August 2008. If students started preparing for the ACT in the previous academic year then the 2009-10 academic year onwards would be the correct post-policy period. As a robustness check, we analyze how moving the post-policy period to 2010-2013 instead of 2009-2013 affects our results.

2.3. The Internet and School-Related Work

According to the National Center for Education Statistics (NCES), 85% of public schools in the U.S. had access to broadband connections in 2001. The push to ensure universal Internet access in schools came due to FCC's 'E-rate' program, launched in 1996. Hence, since the early 2000s, the Internet has been an integral part of work done in schools as well as of take-home school assignments. While there is near-universal Internet connectivity in U.S. schools, actual usage is lower. As was documented in a Pew research study in 2005, 78% of students in the survey sample used the Internet at school. But conditional on using the Internet at school, they almost always use it outside school as well. In 2009, the FCC reported that 70% of all teachers in public schools assigned homework which required the use of the Internet.[10] About 65% of students use the Internet at home to finish assignments, which could also include time spent connecting with teachers or other students in discussion

[9] The link to the passage is here: https://www.kaptest.com/study/act/act-science-conflicting-viewpoints/
[10] See http://neatoday.org/2016/04/20/the-homework-gap/ for more.

boards.

Given the central role the Internet plays in school instruction and homework, analyzing how test scores respond to the law and vary based on Internet penetration serves as a natural starting point.

2.4. Balkanization vs. Broadening of Horizons on the Internet

The important role the Internet plays in school instruction and homework assumes a different dimension in the context of the Louisiana Science Education Act.

Despite the growth of political and religious content on the Internet, it is unclear whether such information leads to a broadening of horizons which would encourage more accurate beliefs, or to greater ideological segregation which could prop up inaccurate beliefs. Sunstein (2001) forcefully argued that with the vast amount of content available online, people would restrict themselves to information consistent with their existing facts and beliefs. Moreover, he points out that this would be most relevant to people from different political ideologies, with liberals potentially only interacting with other liberals and similarly for conservatives. Van Alstyne and Brynjolfsson (2005) also argue that the Internet could either lead to a global village online or cyber-balkanization based on how individuals choose to use its plethora of information.

The law's effect on the actual curricula taught by different schools depended on local religious or political preferences. One potential hypothesis is that areas with lower parental education levels were more likely to have a taste for creationist instructional materials.

Furthermore, if the Internet does play a role in this process then we should expect to see heterogeneous effects of the law depending on the level of Internet penetration (or usage). We hypothesize that higher Internet penetration being associated with science test scores would provide us with suggestive evidence of people seeking out creationist information on the Internet in line with what was being taught in the classroom. On the other hand, if higher Internet penetration leads to higher test scores, all else equal, then this would be indicative of information online being used to broaden horizons.

3. Data

For our empirical analysis we use data on: i) ACT scores, ii) Internet penetration, iii) School district level finances, and iv) other socio-economic indicators at the school district level.

3.1. School Level ACT Scores

We obtain comprehensive school-level ACT scores from the State Education Boards of Texas and Louisiana from 2003 to 2013.[11] For each academic year, we have information on the average ACT grade achieved in each school separately for Science, Math, English and Reading. To ensure confidentiality of student information, average scores are not made available for schools in Texas with fewer than five students taking the ACT in a particular year; in Louisiana, average scores are unavailable for schools with fewer than ten ACT students in a particular year. Each test is graded on a scale of 1-36. The average Science score over the sample period across all schools is 19.76. The mean test scores across different subjects are very similar, at 19.88 for Math, 19.74 for Reading and 18.78 for English.

3.2. Internet Penetration

To arrive at a measure of Internet penetration or connectivity, we use data on the number of high speed Internet service providers (ISPs) in a zip code made available by the FCC (through Form 477). A provider is counted if there is at least one subscriber in the zip code. This data is available only till 2008 and hence we use the number of ISPs at the end of 2007, which is right before the law was enacted, as a measure of Internet penetration. The mean number of ISPs in a zip code is 9.33, with 9 being the median. If the number of high speed ISPs is greater than zero but less than 3, then the exact number is not available in the data. Following Larcinese and Miner (2012), we normalize this to 2, which is the average.

The number of ISPs appears a good proxy for overall Internet adoption and usage. Kolko (2010) uses survey data from Forrester Research to find that there is a monotonic relationship between the number of high speed ISPs and the rate of Internet adoption across zip codes in the United States.

Larcinese and Miner (2012) also find a similar relationship between penetration and usage based on FCC data. While formally the number of ISPs is a measure of Internet penetration, because it is highly correlated with usage, we use it as a plausible proxy for Internet adoption.

There is reason to think that the variation in Internet adoption, after controlling for differences in observable demographics, at the end of 2007, is a somewhat exogenous pro-

[11] For a large majority of the sample period, this data is publicly available, while for the missing years it was made available by the Boards upon request.

cess. Cross-sectional variation in Internet adoption, conditional on observables, is often driven by exogenous factors such as weather, terrain, pre-existing telecommunication cables and right of way laws (see Kolko (2010), Larcinese and Miner (2012), Belo et al. (2013) and Gavazza et al. (2015)). We expect school fixed effects to capture much of this variation.[12]

3.3. Google Trends

We use data from Google Trends on the online search intensity of keywords related to creationism and evolution. Google Trends provides historical search volume data at various geographic levels. We use state level keyword search to ensure that there is sufficient volume of searches. While search intensity at finer geographic levels would be desirable, there are not enough searches at those levels for a large number of keywords for the Google Trends algorithm to report statistics. It is important to note that Google Trends does not report the absolute volume of searches, but only an index ranging from 0 to 100 which is based on the number of queries of the words in question relative to the overall number of queries over a period of time in a geographical area. Hence, we can only make qualitative statements about the direction of change in search intensity. Despite this shortcoming, Google Trends data has been used in various studies to measure consumer interests (Choi and Varian (2012), Wu and Brynjolfsson (2009)), as well as public attitudes (Stephens-Davidowitz, 2014).

3.4. School District Finances

Information on finances such as total revenues and expenditures accruing to schools in a district, is publicly available at an annual level. The U.S. Census Bureau collects such fiscal data as part of the Annual Survey of Government Finances. We use these variables as controls in our regressions. This data also provides detailed information on different sub-categories of revenue and expenditures, which we use in some of our placebo checks. Annual estimates on the number of children and the number of children in poverty in a school district is collected by the Census Bureau as part of the Small Area Income and Poverty Estimates program (SAIPE). A school district on average has about 24,000 children.

[12] In line with this hypothesis, we carry out placebo checks below which show that, conditional on a variety of fixed effects and controls, the underlying demographic characteristics of the school district do not affect test scores in the same way as high rates of Internet penetration or adoption do.

3.5. Other Socio-Economic Variables

We use the American Community Survey (ACS), administered by the U.S. Census Bureau, to get information on other economic and demographic characteristics at the level of the school district. The ACS provides information on the racial composition, adult education and income levels of the school district. The ACS does not take place annually, and hence we use time-invariant 2007 levels of these variables to control for differences in these characteristics across school districts. On average, a school district has 18% of its adult population with less than a high school degree. We use this measure of educational qualification and its variation across districts to analyze how the law had heterogeneous effects depending on the level of education in a district. In terms of ethnic composition, the average school district is 75% White, while African-Americans account for 11% of the population on average. We control for these differences in racial composition of school districts in our regressions and also use them in robustness checks of the baseline results.

4. The Empirical Framework

To analyze how the introduction of the Science Education Act influenced science test scores in Louisiana, we use a difference-in-differences setup with schools in Texas serving as the control group and estimate the following baseline specification:

$$\Delta Science_{it} = \alpha_i + \beta_t + \theta_1 Louisiana_i \times After_t + \theta_2 X_{dt} + \theta_3 Z_d \times After_t + \varepsilon_{it}$$

The outcome variable of interest $\Delta Science_{it}$ is the change in science test scores in state i in year t relative to year $t-1$. The first difference dependent variable in the baseline specification is chosen in line with the literature following Goolsbee and Guryan (2006) and Belo et al. (2013). α_i are school fixed effects which capture any time-invariant differences across schools, in particular, the way science might be taught across schools. β_t are year fixed effects which capture aggregate trends affecting both Louisiana and Texas, such as a change in a federal policy linked to education. Our coefficient of interest is θ_1, which captures the effect of the education policy on science scores in Louisiana schools relative to those in Texas, which did not experience the policy change. The main effect of $After_t$ is collinear with year fixed effects and hence gets dropped from the regression. Similarly, the direct effect of *Louisiana* is collinear with school fixed effects and is thus dropped from the regression.

We include two sets of controls which vary at the level of the school district (d) to account for differences in socio-economic characteristics across districts. X_{dt} consists of the child population, total education revenue and expenditure, which vary at the level of the district-year. Z_d consists of time-invariant controls (at 2007 levels) including the proportion of Whites, the proportion of African-American, median household income, the proportion of the population which has less than a high school degree, the proportion of the population which has some education qualification, the ratio of poor income to the average income, and the number of Internet providers.

Finally, in order to account for the error term being serially correlated between schools within a particular school district, even after accounting for school fixed effects, we cluster standard errors at the school district level. This ensures that we do not overestimate the precision of our results.[13]

5. Benchmark Results, Placebos and Mechanism

5.1. Baseline Estimates

5.1.1. Estimates for the Full Sample

We begin our analysis with the main specification (1) to evaluate the effect of the Science Education Law in Louisiana on the change in science test scores in Louisiana schools relative to those in Texas. The main independent variable of interest is the interaction term of whether the school is in Louisiana and whether it is a post-policy period.

The baseline results for the whole sample, displayed in Table 2, show a decline in science test scores in Louisiana relative to Texas. In column (1), which has no controls, Louisiana $\times$ After is negative and statistically significant at the 1% level. As we add year fixed effects (column (2)), socio-economic variables (column (3)) and school fixed effects (column (4)), the effect remains statistically significant at conventional levels. Once we add both year and school fixed effects in column (4), only the interaction effect remains, since the direct effects of both Louisiana and After get absorbed by the two sets of fixed effects. In terms of the magnitude of the effect for the whole sample, the law reduces test scores by 0.12

[13] Clustering at the level of the city, identified through the second and the third digits of the zip code, or at the state $\times$ year level leaves the results unchanged as reported in Table 14.

of a standard deviation in our most stringent specification (column (5)). While we follow the literature in the functional form used for the dependent variable, we also look at alternative functional forms to assess the stability of our results. In column (6), we use science scores in levels instead of ΔScience to find similar results. In column (7), we use the science score as a proportion of the total as the dependent variable, finding qualitatively similar results to when we use ΔScience.

5.1.2. Test Scores by Internet Penetration and Parental Education

After establishing results for the full sample, we report estimates which form the core of our paper focusing on how the effect of this law varies across different areas with different levels of Internet penetration and adult (or parental) education.[14] In particular, what role does the Internet play in this process? Does access to information online mitigate or exacerbate the effect of the law? Does the law hurt students who come from areas with low levels of parental education? These questions are of first-order importance because of the widespread use of the Internet in school-related work. In particular, students seeking out information online which is consistent with classroom creationist teachings could harm their academic performance. Moreover, it is well documented that the level of parental education influences their children's outcomes, and hence would affect the effect of the law.

Results in Table 3 provide a clear picture on both these issues. When we split the sample into high Internet and low Internet areas (i.e., the number of Internet providers is above and below the median respectively), we find that Louisiana $\times$ After term is negative and statistically significant only for high Internet areas (column (1)) and insignificant for low Internet areas (column (2)). Moreover, in low education areas with high Internet penetration, the law had a statistically significant negative effect (at the 1% level) on science test scores of schools in Louisiana relative to those in Texas (column (3)). In terms of the magnitude, a coefficient of -0.608 corresponds to approximately half a standard deviation decline in science test scores.

Quantitatively, these estimates are in line with those found in (Belo et al., 2013), who also document a 0.7 standard deviation decline in student scores due to the availability of the Internet. We do not find any statistically significant effect of the education law on test scores

[14] We use variation in adult education across different regions as a measure of family (education) quality rather than school quality. The two would, of course, be correlated.

in low education and low Internet penetration areas (column (4)), which indicates that the Internet does indeed play a vital role in the ways students access and use information related to school work. The size of the coefficient (-0.284) is also less than half of what we found for schools in high Internet regions. Moreover, when we analyze areas with low income levels and high (and low) Internet penetration, we do not find statistically or economically significant results (columns (5) and (6)), unlike what we find for low education and high Internet areas. This indicates that, as we hypothesized, it is the interaction of low education and access to the Internet which seems to be driving the effect. Results for high education regions show that the law had no statistically significant effect on science test scores irrespective of whether there was high Internet penetration (column (4)) or low Internet penetration (column (5)). This is in line with intuition, as one would expect families with strong educational backgrounds to ensure that their children are not adversely affected in any nationally administered test due to a policy shift at the state level. Quantitatively, the coefficients are also a fraction (-0.165 and 0.112 in columns (4) and (5) respectively) of the effect found for regions with low education and high Internet.

Finally, we provide some graphical evidence in Figure 2 which complements our baseline regression results. Focusing on areas with high Internet penetration and low levels of education, we plot the coefficients of a regression of the change in science test scores in schools in Louisiana relative to Texas before and after the policy, conditional on school and year fixed effects and a few controls. There are two main takeaways from this picture. First, before the policy there is no evidence of any systematic differences in science test scores between Louisiana and Texas schools. In other words, there are no pre-trends. Second, it is clear that after the law was introduced in Louisiana, science scores in Louisiana schools relative to Texas fell in a statistically significant way.

5.2. Placebo Checks

Our identifying assumption is that the trends in science test scores (and other variables) of schools in Louisiana relative to Texas would have remained the same in the absence of the Science Education Law being passed in Louisiana. This assumption cannot be tested directly, but we do carry out a series of placebo checks to ensure that the results from our data are consistent with the identifying assumption.

5.2.1. Effect on Math and other subject scores

Since the law was mainly aimed at influencing the teaching of science in classrooms, if we are indeed capturing the causal effect of the law, we should not see a similar change in other subject test scores. In particular, an important check in our favor would be to rule out any effect on math test scores which would indicate that there was no general tendency of Louisiana schools to under-perform in analytical subjects around the time of the law being passed. Relatedly, analyzing whether the law had an effect on math test scores, especially in regions with high Internet penetration, would be a check on whether high Internet usage served as a general distraction, hindering performance across different subjects in line with what Belo et al. (2013) find looking at Portuguese schools. Our hypothesis would indicate that we should not find any effect of the law on math test scores in low education and high Internet penetration regions.

Table 4 shows the results of this placebo check. We can see that the law had no effect on math test scores as Louisiana $\times$ After is insignificant. This holds for the full sample (column (1)) as well as low education and high Internet penetration regions (column (2)), which were driving the reduction in science test scores in our baseline results. This gives us confidence that the presence of the Internet is not leading to a general decline in test scores, but that there is an effect specific to science related performance. Moreover, reassuringly, there is also no change in math test scores in other regions as well (columns (3)-(5)).

As a further check, we look at the policy's effect on English and Reading test scores in Louisiana relative to Texas. The results reported in Tables 5 show that there was no change in test scores post the policy. This holds for the whole sample (column (1)) and in particular for low education and high Internet regions (column (2)). Other regions (columns (3)-(5)) also do not experience any change in these test scores.

This gives us further confidence that we are indeed picking up something relevant to the effect of the law on science instruction in Louisiana classrooms and that the Internet played a role in the decline of science test scores but did not have a negative effect on performance across all subjects.

5.2.2. False Policy Dates

We now analyze our results related to low education and high Internet penetration areas in more detail. In particular, we want to assess whether these regions were inherently more likely to fare worse than schools in Texas with similar characteristics. Figure 1 shows that since there were no pre-trends, there was no systematic difference between schools in such regions across the two states. We examine this further by analyzing data from the pre-policy years and assigning the policy year to each of those pre-policy years one by one to see whether we can generate the same results as we do with the actual post-policy data.

The results in Table 6 give us confidence in our estimates. When the policy year is assigned to 2004 (column (1)), implying that the post-policy period is 2005-2008, we do not see any statistically significant effect of the policy on Louisiana science test scores relative to Texas. Additionally, the sign of the coefficient is positive, which would go against our hypothesis that these regions in Louisiana were prone to performing relatively worse in science tests. We find similar null results when the policy year is assigned to 2005 (column (2)), to 2006 (column (3), and finally to 2007 (column (4)).

Overall, these results, along with Figure 1, suggest that regions with high Internet penetration but low levels of education in Louisiana were not systematically underperforming in their science tests relative to their Texas counterparts in the pre-policy period.

5.2.3. Placebo Check with Socio-Economic Observables

As a final check to assess whether we are indeed capturing the causal effect of the Science Education Law on test scores in Louisiana, we investigate whether there were any discontinuous changes in other observables at the same time as the law was passed. This could imply that we are merely picking up the effect on science test scores of some other observable, which is moving at the same time as the education policy was changed. Alternatively, there could be a related unobservable which affects both the observable and test scores, for example a general change in attitude towards the sciences.

We estimate the baseline specification while altering the outcome variable of interest in every column in Table 7 as a falsification test. In column (1) where the outcome variable of interest is the total population in the school district, we find that the coefficient on Louisiana $\times$ After is statistically insignificant. In column (2), we find a similar null effect when the dependent variable is the total number of children in the school district, which we also explicitly control for in all our regressions. In columns (3) and (4), we find no statistically significant change in total revenue or total expenditure of Louisiana schools after the law was passed. In columns (5) and (6), we look at certain sub-categories of sources where the school district is getting its revenue from. In column (5), we find that there was no change in the amount of revenue earmarked for science related activities at the school district level. Moreover, there was no change in the amount of local revenue generated (column (6)) for the school district after the law was passed in Louisiana.

Overall, while we cannot test our identifying assumption directly, the placebo checks suggest that unobserved heterogeneity and events happening simultaneously are not driving our key findings.

5.3. Test Scores, Demographics and Google Search

5.3.1. Test Scores and Demographics

Our baseline results indicate that interactions between higher Internet usage and low levels of education are part of the mechanism which drives the decline in test scores. While this provides suggestive evidence for the Internet and education playing a significant role in the process, it is also true that these factors can be correlated with a variety of underlying demographic characteristics of the regions which might drive the results. Hence, we carry out a set of checks to assess whether our results are being driven by population size or density, commuting times or income, or simply reflect a metropolitan-non metropolitan area divide.

In Table 8, in columns (1) and (2), we show that neither high nor low population can generate the same results as high Internet penetration. Similarly, differential levels of child population are not drivers of results which are observationally equivalent to those generated by high Internet penetration areas since the coefficient on Louisiana $\times$ After is statistically insignificant in both columns (3) and (4). The coefficient on Louisiana $\times$ After is insignificant when we split the sample based on high population density (column (5)) and low population density (column (6)) as well as high and low commuting times (columns (7) and (8) respectively). Columns (9) and (10) show that the high Internet results cannot be generated by simply looking at metropolitan and non-metropolitan areas separately. We also find that different levels of Internet penetration does not reflect an income divide with the coefficients for both high income (column (11)) and low income (column (12)) being insignificant. Finally, we also look at high and low levels of education to find that, as in the baseline, high education areas remain unaffected by this law (column (13)). In low education areas, the effect of the law is negative and statistically significant (column (14)) as in the case of high Internet penetration areas.

This shows that there is an interaction between low levels of education and the availability of information online due to high Internet penetration which leads to a decline in science test scores. More generally, these results suggest that we are measuring something meaningful about the synergies between Internet use and education which is not confounded by, and goes beyond, other underlying demographics of the different school districts.

5.3.2. Google Trends for Creationism Search Terms

Our baseline results have demonstrated the negative effect of the Science Education Act on science test scores in Louisiana schools. Our results suggest that the Internet did have an adverse effect on test scores by potentially leading to information silos online rather than broadening students' horizons. To highlight this mechanism cleanly, we would require Internet browsing data at the level of the household and school (for both parents and students), which unfortunately is unavailable. In the absence of this detailed data, we consider an alternative way to pin down the mechanism.

We provide evidence for the Internet being used to confirm creationist teachings in the classroom by analyzing Google Trends data. A simple Google search shows how there is easy access to information in line with creationist theories. For example, in Figure 3, we show how a Google search for 'Intelligent Design' brings up results which highlight the case for the 'Science of Intelligent Design' while Figure 4 shows how the second-ranked search result, after its Wikipedia entry, www.intelligentdesign.org tries to debunk evolution.

We use state-level search intensity on keywords associated with creationism and evolution before and after the law was initiated in the Louisiana legislature.[15] Due to insufficient search intensity at finer geographic levels, we use state level queries to provide model-free evidence to test our hypothesis. In particular, our hypothesis of access to the Internet allowing people to seek out creationism-related information, due to creationism being taught in the classroom, would imply that we should see an increase in creationism-related search intensity in Louisiana relative to Texas after the law was instituted relative to before. We create a list of creationism- and evolution-related search terms which we validate and supplement

[15] We focus on three years before and after the policy, and in particular we define the pre-policy period from 05/01/2005 to 05/01/2008 and the post-policy period from 05/02/2008 to 05/01/2011. It is in May 2008 that it became clear that the Louisiana Science Education Act would come into effect, since it was passed by the Senate on 04/28/2008. Results are robust to alternative cutoffs. For more on the different stages of the passage of the bill, see https://www.aibs.org/public-policy/evolution_state_news

based on a Google keyword rank checker tool.[16]

Table 9 shows that the search intensity of creationism-related keywords provide evidence in line with our hypothesis. In particular, the search intensity for 'Creationism' before the law was 10 in Louisiana and 8 in Texas ($\delta_b = 2$) while after the law it was 12 for Louisiana and 6 for Texas ($\delta_a = 6$), which implies that search intensity between Louisiana and Texas, after the law increased with $\delta_a - \delta_b = 4$. We find similar results for search terms such as 'Intelligent Design' ($\delta_a - \delta_b = 2$) which is essentially a synonym for creationism. Other keywords terms related to creationism also see an increase in search intensity, such as 'Young Earth Creationism', 'Flat Earth' and 'Book of Genesis'. Terms which are related to religiosity in general, such as 'Bible', 'Christianity' and 'Catholic Church' also saw an increase in search intensity. This is in line with the idea that creationism is primarily a religious theory, the teaching of which can lead to an increase in religiosity in general.

A concern with this model-free evidence could be that it is possible that search intensity for all kinds of terms went up in Louisiana relative to Texas after the law. In particular, we would like to rule out that search intensity for keywords related to evolution also increased after the law. Reassuringly, we find that evolution-related terms such as 'Homo Sapiens', 'Human Evolution', 'DNA', 'Adaptation' and 'Darwin' either stayed constant or declined in search intensity.

As an additional check, we first take a subset of our keyword list and run a difference-in-differences regression with Google search data aggregated at the state level with year and state fixed effects using the whole sample period (2004-2013). Results in Table 10 are in line with our model-free evidence. There was a statistically significant increase in 'Creationism' searches in Louisiana relative to Texas after the policy change (column (1)). Similarly, there is a statistically significant increase in search intensity for 'Intelligent Design' (column (2)), 'Christianity' (column (3)), 'Bible' (column (4)) and 'Church' (column (5)). In column (6), we group all creationism-related keywords together and run the same difference-in-differences regression by additionally allowing for keyword fixed effects. The coefficient on Louisiana $\times$ After is positive and statistically significant at the 1% level. Finally, in column (7), we take all creationism- and evolution-related terms and analyze the triple interaction term Louisiana $\times$ After $\times$ Creationism Words. The coefficient is positive and statistically significant at the 1% level, implying that there was an increase in searches related to cre-

[16] In particular we use serps.com, which provides keyword ranks related to a search term in Google.

ationist keywords relative to evolution-related words after the law in Louisiana.

Overall, analyzing the Google Trends data provides suggestive evidence in line with our hypothesis that Internet users in Louisiana were seeking out information related to creationism which was allowed to be taught in classrooms after the Science Education Act was passed.

6. Robustness Checks

6.1. 2009 as the Policy Year

So far, in our analysis, we have treated 2008 as the policy year with 2009-2013 being the post-policy period. The policy was passed in June 2008, which could imply that students taking the ACT in the 2008-09 academic year might not be severely affected by classroom instruction since preparations for the ACT start a little in advance. To ensure that our results are robust to this concern, we re-run the baseline estimation using 2009 as the policy year with 2010-2013 serving as the post-policy period. Table 11 shows that these results are in line with our baseline estimates. Only areas with high Internet penetration and low education experience a statistically significant (at the 1% level) decline in science test scores. The coefficients are quantitatively similar to the baseline as well. Moreover, no other region experienced a similar significant decline in science test scores in the 2010-2013 post policy period.

6.2. Using Counties Near The Louisiana-Texas Border

Our difference-in-differences approach goes a long way in addressing potential endogeneity concerns and establishing the causal effect of the law in Louisiana on science test scores. School fixed effects and other time-varying control variables account for a variety of factors which could be driving the observed result. Moreover, our placebo checks bolster our causal claims. Nevertheless, the fact that the enforcement of the law depends on the potentially changing characteristics of schools means that endogeneity remains a concern since we can't observe all the relevant variables that could simultaneously determine a change in our outcome variables around the time the law was passed.

To test the robustness of our results, we take an additional step by focusing on a subsample of the data which consists of schools located in only those counties which lie close to the Texas-Louisiana border. The underlying assumption is that the schools in these counties would be more similar in their unobservable characteristics relative to all schools across the two states. We restrict our attention to approximately one quarter of the sample to ensure we have enough observations in these counties to assess the heterogeneity of the law's effects, which maps back into our baseline estimates. Using this sub-sample of schools in counties close to either side of the Louisiana-Texas border, we estimate our baseline specification again.

The results in Table 12 show that the estimates based only on schools in these counties is qualitatively similar to what we find in the full sample. The law has a negative and significant effect on science test scores in low education and high Internet penetration areas (column (1)). Additionally, the law has no effect on science test scores of schools in these border counties in areas with low education and low levels of Internet (column (2)), with high education and high Internet levels (column (3)) and high education and low Internet levels (column (4)). These results, which look at schools in more geographically proximate areas across Louisiana and Texas, are in line with the baseline estimates, providing more confidence in our causal claims.[17]

6.3. Excluding Outliers

Finally, we also analyze whether our baseline results are robust to the exclusion of outliers and to different functional forms.

In column (1) of Table 13, we drop schools with science test scores above the 95th percentile in low education and high Internet penetration regions while estimating the baseline equation. The coefficient on Louisiana $\times$ After is still negative and statistically significant at the 1% level. Similarly, when we drop schools in the bottom 5th percentile (column (2)), results remain qualitatively and quantitatively in line with the baseline.

Next, while considering high Internet penetration areas, we drop schools in areas with Internet penetration above the 95th percentile (column (3)) and below the 5th percentile (column (4)) with no qualitative difference in the effect of the policy relative to our benchmark.

[17] Our results are also robust to explicitly excluding schools in the New Orleans area which took steps to prohibit the teaching of Creationism and Intelligent Design as part of the Science curriculum in 2012. For details see https://ncse.com/news/2012/12/louisiana-board-bans-creationism-0014665. Results available upon request.

To ensure that our results are not driven by a particular year, we drop observations from 2013. Column (5) indicates that 2013 does not exclusively drive the results, since Louisiana $\times$ After is still negative and statistically significant (at the 5% level). In column (6), we drop 2004 and find similar results.

7. CONCLUSION

In this paper, we quantify the effect of the Louisiana Science Education Act on student performance in nationally administered science tests. We also analyze how this effect varies by the degree of Internet penetration across different areas. Using Texas schools as the control group, we find that the law had a negative and statistically significant effect on science test scores in Louisiana, but that this effect is limited to less-educated regions with high levels of Internet connectivity. We establish that this effect is causal by demonstrating that the law did not affect performance in other subjects. Moreover, we use placebos to demonstrate that there was no similar effect in the pre-policy period and that we do not see any movement in other observables which rules out unobservable factors driving our results. To identify the mechanism, we find that creationism-related search terms online increased significantly in Louisiana relative to Texas after the policy was introduced. This increase in online search was also relative to a baseline of evolution-related search terms. Moreover, we show that the decline in test scores in high Internet areas cannot be generated by characteristics such as population size, density or income, or by whether the area is metropolitan or not, implying that the Internet is not a mere proxy for some underlying demographic attribute of the region. Overall, this provides suggestive evidence that information online is being used to seek out information related to creationist teachings in the classroom .

Our study has limitations, especially related to data availability. First, while we attribute the decline in test scores to teaching in the classrooms, we do not observe exactly what was taught in classrooms. Further research and more detailed data is required to directly pin down the effect of different teaching tools on student performance. Second, we do not have Internet penetration data for the entire sample period and hence we analyze the heterogeneity in the effect on test scores using cross-sectional variation in Internet availability. Finally, the science curriculum has often been improved in various ways across different U.S. states or school districts. Whether our study generalizes to these other states could be analyzed by future research. Notwithstanding these limitations, this paper represents a useful first step in understanding the interaction between the ability of the Internet to reinforce or change the set of beliefs that a person adopts.

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TABLE 1: SUMMARY STATISTICS

	Observations	Mean	Std. Deviation	Min.	Max.
Science Test Score	13,741	19.76	1.93	9.2	29
ΔScience Test Score	12,286	.014	1.27	-9.9	10.3
Math Test Score	13,741	19.88	2.17	13	30
Reading Test Score	13,741	19.74	2.41	10.7	34
English Test Score	13,723	18.78	2.53	7	36
District Education Revenue	13,723	204636.5	389838.5	666	2221585
District Education Expenditure	13,741	213542.5	410812.2	580	2355857
Child population	13,531	24127.59	47418.84	27	266882
No. of Internet Providers	11,499	9.33	2.87	2	16
Prop. of White	13,741	0.76	0.15	0.18	1
Prop. of African-American	13,741	0.11	0.12	0	0.73
Prop. with Less than High School Degree	13,741	0.18	0.10	0	0.62
Prop. with some education degree	13,741	0.30	0.07	0.08	0.62
Household Income	13,741	30576.28	8666.98	11586	109907
Ratio of Poor Income to Average Income	13,741	0.17	0.07	0.02	0.49

TABLE 2: BASELINE RESULTS: SCIENCE TEST SCORES

VARIABLES	(1) ΔScience	(2) ΔScience	(3) ΔScience	(4) ΔScience	(5) ΔScience	(6) Science	(7) $\frac{Science}{Total}$
Louisiana × After	-0.322***	-0.322***	-0.241***	-0.174***	-0.162**	-0.220**	-0.0016***
	(0.0290)	(0.0290)	(0.0459)	(0.0616)	(0.0789)	(0.087)	(0.0005)
Louisiana	0.0491***	0.0491***	0.122***				
	(0.0165)	(0.0165)	(0.0460)				
After	0.0711***						
	(0.0176)						
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
School FE	No	No	No	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes	Yes	Yes	Yes
Controls × Internet	No	No	No	No	Yes	Yes	Yes
Observations	13,680	13,680	12,077	12,077	10,124	11,338	11,338
R-squared	0.003	0.013	0.124	0.273	0.288	0.760	0.398

Robust standard errors in parentheses clustered by school district. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is a school's average science test score in first differences in columns (1)-(5), in levels in column (6) and as a proportion of the total score in column (7). Controls include the number of Internet providers, school district revenue, school district expenditures, school district test scores in other subjects, child population, proportion of African-Americans, proportion of Whites, average household income, proportion with less than high school degree, proportion with some degree, average ratio of poor income to the average income. Column (7) does not include school district test scores in other subjects as a control since the dependent variable is a normalized measure.

TABLE 3: BASELINE RESULTS: HETEROGENEITY IN SCIENCE TEST SCORES

VARIABLES	High Internet (1) ΔScience	Low Internet (2) ΔScience	Low Educ+High Int (3) ΔScience	Low Educ+Low Int (4) ΔScience	Low Income+High Int (5) ΔScience	Low Income+Low Int (6) ΔScience	High Educ+High Int (7) ΔScience	High Educ+Low Int (8) ΔScience
Louisiana × After	-0.247***	-0.0963	-0.608***	-0.284	-0.055	-0.037	-0.165	0.112
	(0.0835)	(0.149)	(0.183)	(0.204)	(0.225)	(0.181)	(0.103)	(0.247)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls × Internet	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,793	4,331	2,972	2,151	1,498	3,431	2,821	2,180
R-squared	0.227	0.332	0.213	0.311	0.336	0.339	0.267	0.363

Robust standard errors in parentheses clustered by school district. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is a school's average science test score in first differences. Controls include the number of Internet providers, school district revenue, school district expenditures, school district test scores in other subjects, child population, proportion of African-Americans, proportion of Whites, average household income, proportion with less than high school degree, proportion with some degree, average ratio of poor income to the average income.

TABLE 4: PLACEBO: MATH TEST SCORES

VARIABLES	Full Sample (1) ΔMath	Low Educ+High Int (2) ΔMath	Low Educ+Low Int (3) ΔMath	High Educ+High Int (4) ΔMath	High Educ+Low Int (5) ΔMath
Louisiana × After	0.0315	-0.179	0.106	0.0852	0.243
	(0.0773)	(0.186)	(0.215)	(0.110)	(0.219)
Year FE	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Controls × Internet	Yes	Yes	Yes	Yes	Yes
Observations	10,124	2,972	2,151	2,821	2,180
R-squared	0.247	0.186	0.292	0.226	0.290

Robust standard errors in parentheses clustered by school district. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is a school's average math test score in first differences. Controls include the number of Internet providers, school district revenue, school district expenditures, school district test scores in english and reading, child population, proportion of African-Americans, proportion of Whites, average household income, proportion with less than high school degree, proportion with some degree, average ratio of poor income to the average income.

TABLE 5: PLACEBO: ENGLISH AND READING TEST SCORES

VARIABLES	Full Sample (1) Δ(English+Reading)	Low Educ+High Int (2) Δ(English+Reading)	Low Educ+Low Int (3) Δ(English+Reading)	High Educ+High Int (4) Δ(English+Reading)	High Educ+Low Int (5) Δ(English+Reading)
Louisiana × After	0.158	-0.228	-0.493	0.422	0.411
	(0.219)	(0.451)	(0.634)	(0.322)	(0.807)
Year FE	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Controls × Internet	Yes	Yes	Yes	Yes	Yes
Observations	10,124	2,972	2,151	2,821	2,180
R-squared	0.247	0.186	0.292	0.226	0.290

Robust standard errors in parentheses clustered by school district. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is a school's average english and reading test scores in first differences. Controls include the number of Internet providers, school district revenue, school district expenditures, school district test scores in math, child population, proportion of African-Americans, proportion of Whites, average household income, proportion with less than high school degree, proportion with some degree, average ratio of poor income to the average income.

TABLE 6: PLACEBO: FAKE POLICY DATES FOR HIGH INTERNET AND LOW EDUCATION AREAS

VARIABLES	Year=2004 (1) ΔScience	Year=2005 (2) ΔScience	Year=2006 (3) ΔScience	Year=2007 (4) ΔScience
Louisiana × After	0.278	0.152	-0.214	0.0908
	(0.277)	(0.228)	(0.271)	(0.347)
Year FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Controls × Internet	Yes	Yes	Yes	Yes
Observations	1,470	1,470	1,470	1,470
R-squared	0.267	0.271	0.268	0.264

Robust standard errors in parentheses clustered by school district. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is a school's average science test score in first differences. The sample is restricted to 2008 which is the pre-policy period. Controls include the number of Internet providers, school district revenue, school district expenditures, school district test scores in other subjects, child population, proportion of African-Americans, proportion of Whites, average household income, proportion with less than high school degree, proportion with some degree, average ratio of poor income to the average income.

TABLE 7: PLACEBO: OTHER OBSERVABLES FOR HIGH INTERNET AND LOW EDUCATION AREAS

VARIABLES	(1) Overall Population	(2) Child Population	(3) Total Revenue	(4) Total Expenditure	(5) Revenue for Science	(6) Total Local Revenue
Louisiana × After	-4,043	1,028	-20,975	-12,407	595.8	2,329
	(4,103)	(1,471)	(22,840)	(17,001)	(382.1)	(9,683)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Controls × Internet	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,293	3,293	3,293	3,293	3,293	3,293
R-squared	1.000	0.998	0.997	0.995	0.950	0.998

Robust standard errors in parentheses clustered by school district. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Controls include the number of Internet providers, school district revenue, school district expenditures, school district test scores in other subjects, child population, proportion of African-Americans, proportion of Whites, average household income, proportion with less than high school degree, proportion with some degree, average ratio of poor income to the average income.

TABLE 8: SCIENCE TEST SCORES AND DEMOGRAPHICS

	High Population	Low Population	High Child Pop.	Low Child Pop.	High Density	Low Density	High Commute	Low Commute	Metro	Non Metro	High Income	Low Income	High Educ.	Low Educ.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
VARIABLES	ΔScience	ΔScience	ΔScience	ΔScience	ΔScience	ΔScience	ΔScience	ΔScience	ΔScience	ΔScience	ΔScience	ΔScience	ΔScience	ΔScience
Louisiana × After	-0.0754	-0.0852	-0.0707	-0.0799	-0.0876	-0.119	-0.130	-0.0787	-0.0984	-0.104	-0.0300	-0.0856	-0.065	-0.440***
	(0.0848)	(0.160)	(0.0882)	(0.161)	(0.146)	(0.0912)	(0.122)	(0.125)	(0.118)	(0.119)	(0.0876)	(0.1599)	(0.109)	(0.135)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls × Internet	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,247	4,876	5,251	4,872	4,544	5,580	5,101	5,023	6,266	3,858	5,195	4,929	5,001	5,123
R-squared	0.197	0.338	0.196	0.339	0.317	0.247	0.315	0.275	0.273	0.320	0.192	0.337	0.327	0.264

Robust standard errors in parentheses clustered by school district. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable in columns (1) and (2) is high and low levels of total population, in (3) and (4) it is high and low levels of child population, in columns (5) and (6) it is high and low population density, in columns (7) and (8) it is high and low commuting times, whether the zip code is in an urban (column (9)) or rural area (column (10)), and high (column (11)) and low (column (12)) levels of household income. Controls include the number of Internet providers, school district revenue, school district expenditures, child population, proportion of African-Americans, proportion of Whites, average household income, proportion with less than high school degree, proportion with some degree, average ratio of poor income to the average income.

TABLE 9: GOOGLE TRENDS SEARCH INTENSITY

	Before the Law			After the Law			
Search Word	Louisiana$_b$	Texas$_b$	δ_b	Louisiana$_a$	Texas$_a$	δ_a	$\Delta = \delta_a - \delta_b$
Creationism	10	8	2	12	6	6	4
Intelligent Design	5	4	1	13	9	3	2
Young Earth Creationism	2	2	0	4	2	2	2
Bible	7	6	1	15	9	6	5
God	9	8	1	22	11	11	10
Christianity	6	6	0	12	6	6	6
Catholic Church	5	2	3	12	4	8	5
Pope	1	2	-1	9	4	5	6
Flat Earth	0	8	-8	4	4	0	8
Book of Genesis	1	1	0	3	2	1	1
Dinosaur	32	27	5	42	35	7	2
Darwinism	11	7	4	10	5	5	1
Human Evolution	10	6	4	11	8	3	-1
DNA	31	21	10	36	28	8	-2
Adaptation	9	6	3	20	18	2	-1
Darwin	13	6	7	15	9	6	-1
Homo Sapiens	24	16	8	34	26	8	0
Hunter-Gatherer	1	0	1	1	1	0	-1
Genetics	27	15	12	33	22	11	-1
Sexual Selection	1	1	0	2	2	0	0

TABLE 10: GOOGLE TRENDS REGRESSIONS

VARIABLES	Creationism (1) Search Intensity	Intelligent Design (2) Search Intensity	Christianity (3) Search Intensity	Bible (4) Search Intensity	Catholic Church (5) Search Intensity	All Creationism Words (6) Search Intensity	All Words (7) Search Intensity
Louisiana × After	0.692**	0.726***	0.667**	0.610*	1.169***	0.399***	0.0616
	(0.277)	(0.254)	(0.277)	(0.332)	(0.297)	(0.0825)	(0.0772)
Louisiana × After × Creationism Words							0.337***
							(0.113)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Words FE	No	No	No	No	No	Yes	Yes
Observations	242	242	242	242	242	2,904	4,840
R-squared	0.111	0.247	0.353	0.290	0.202	0.398	0.559

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the (logarithm) of Google search intensity related to each term mentioned.

TABLE 11: ROBUSTNESS: ALTERNATIVE POLICY YEAR (2009)

VARIABLES	Low Educ+High Int (1) ΔScience	Low Educ+Low Int (2) ΔScience	High Educ+High Int (3) ΔScience	High Educ+Low Int (4) ΔScience
Louisiana × After	-0.757***	-0.203	-0.240	0.0482
	(0.209)	(0.223)	(0.147)	(0.226)
Year FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Controls × Internet	Yes	Yes	Yes	Yes
Observations	2,972	2,151	2,821	2,180
R-squared	0.216	0.312	0.267	0.362

Robust standard errors in parentheses clustered by school district. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is a school's average science test score in first differences. Controls include the number of Internet providers, school district revenue, school district expenditures, school district test scores in other subjects, child population, proportion of African-Americans, proportion of Whites, average household income, proportion with less than high school degree, proportion with some degree, average ratio of poor income to the average income.

TABLE 12: ROBUSTNESS: COUNTIES NEAR TEXAS-LOUISIANA BORDER

VARIABLES	Low Educ+High Int (1) ΔScience	Low Educ+Low Int (2) ΔScience	High Educ+High Int (3) ΔScience	High Educ+Low Int (4) ΔScience
Louisiana × After	-1.013**	-0.489	-0.0115	0.0460
	(0.454)	(0.628)	(0.182)	(0.315)
Year FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Controls × Internet	Yes	Yes	Yes	Yes
Observations	759	436	801	828
R-squared	0.192	0.369	0.251	0.392

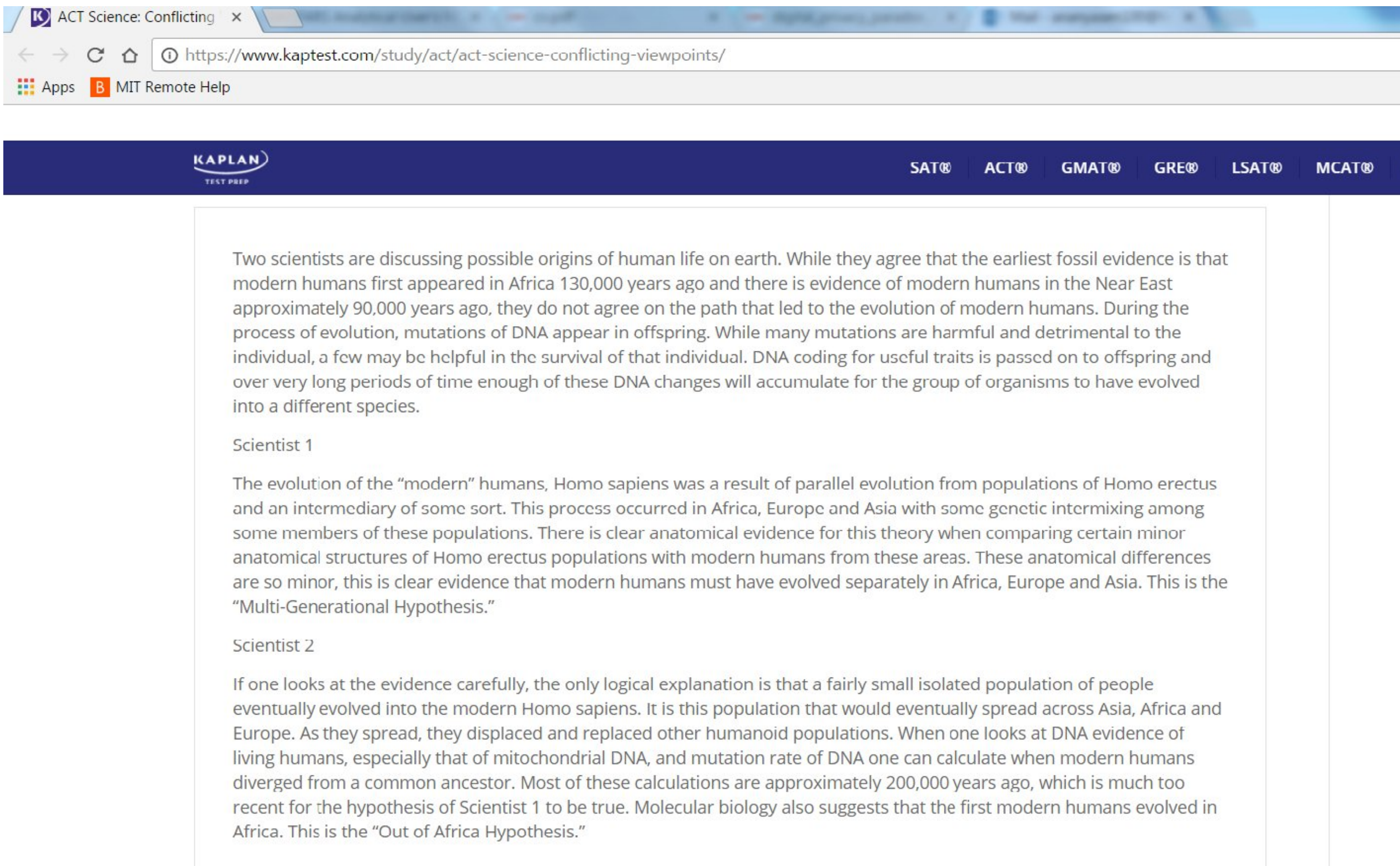
Robust standard errors in parentheses clustered by school district. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is a school's average science test score in first differences. Controls include the number of Internet providers, school district revenue, school district expenditures, school district test scores in english and reading, child population, proportion of African-Americans, proportion of Whites, average household income, proportion with less than high school degree, proportion with some degree, average ratio of poor income to the average income.

TABLE 13: ROBUSTNESS: OUTLIERS

	Exclude Top Scores	Exclude Lowest Scores	Exclude Highest Internet	Exclude Lowest Internet	Exclude 2013	Exclude 2004
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ΔScience	ΔScience	ΔScience	ΔScience	ΔScience	ΔScience
Louisiana × After	-0.565***	-0.687***	-0.600***	-0.453**	-0.421**	-0.624***
	(0.194)	(0.187)	(0.182)	(0.201)	(0.191)	(0.202)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Controls × Internet	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,873	2,645	2,619	2,516	2,681	2,682
R-squared	0.220	0.253	0.228	0.205	0.217	0.222

Robust standard errors in parentheses clustered by school district. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the change in science test scores. Controls in columns (1)-(7), include the number of Internet providers, school district revenue, school district expenditures, school district test scores in other subjects, child population, proportion of African-Americans, proportion of Whites, average household income, proportion with less than high school degree, proportion with some degree, average ratio of poor income to the average income.

FIGURE 1: EVOLUTION RELATED PASSAGE



Two scientists are discussing possible origins of human life on earth. While they agree that the earliest fossil evidence is that modern humans first appeared in Africa 130,000 years ago and there is evidence of modern humans in the Near East approximately 90,000 years ago, they do not agree on the path that led to the evolution of modern humans. During the process of evolution, mutations of DNA appear in offspring. While many mutations are harmful and detrimental to the individual, a few may be helpful in the survival of that individual. DNA coding for useful traits is passed on to offspring and over very long periods of time enough of these DNA changes will accumulate for the group of organisms to have evolved into a different species.

Scientist 1

The evolution of the "modern" humans, Homo sapiens was a result of parallel evolution from populations of Homo erectus and an intermediary of some sort. This process occurred in Africa, Europe and Asia with some genetic intermixing among some members of these populations. There is clear anatomical evidence for this theory when comparing certain minor anatomical structures of Homo erectus populations with modern humans from these areas. These anatomical differences are so minor, this is clear evidence that modern humans must have evolved separately in Africa, Europe and Asia. This is the "Multi-Generational Hypothesis."

Scientist 2

If one looks at the evidence carefully, the only logical explanation is that a fairly small isolated population of people eventually evolved into the modern Homo sapiens. It is this population that would eventually spread across Asia, Africa and Europe. As they spread, they displaced and replaced other humanoid populations. When one looks at DNA evidence of living humans, especially that of mitochondrial DNA, and mutation rate of DNA one can calculate when modern humans diverged from a common ancestor. Most of these calculations are approximately 200,000 years ago, which is much too recent for the hypothesis of Scientist 1 to be true. Molecular biology also suggests that the first modern humans evolved in Africa. This is the "Out of Africa Hypothesis."

FIGURE 2: POLICY IMPACT IN HIGH INTERNET AND LOW EDUCATION REGIONS

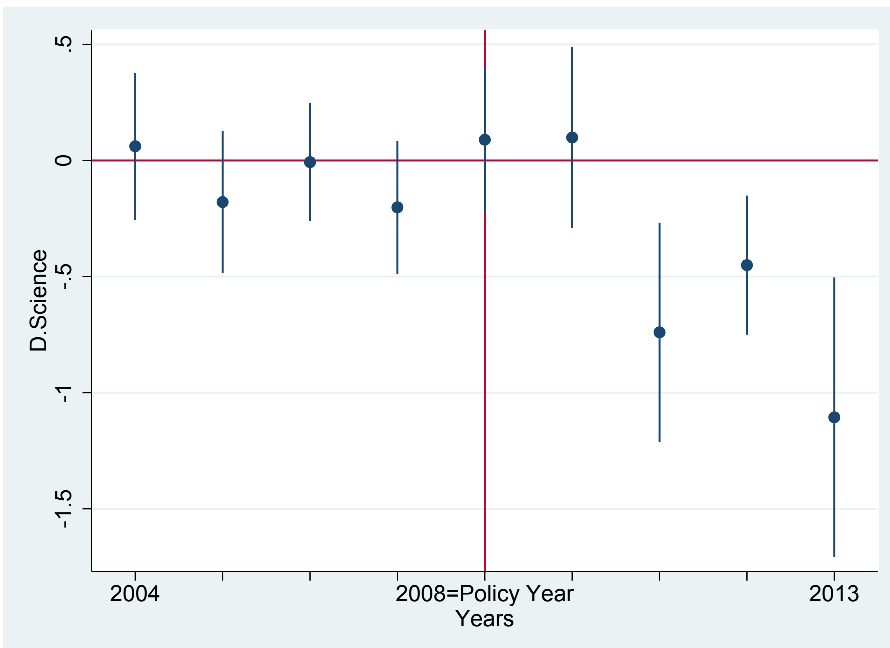


FIGURE 3: GOOGLE SEARCH RESULT FOR 'INTELLIGENT DESIGN'

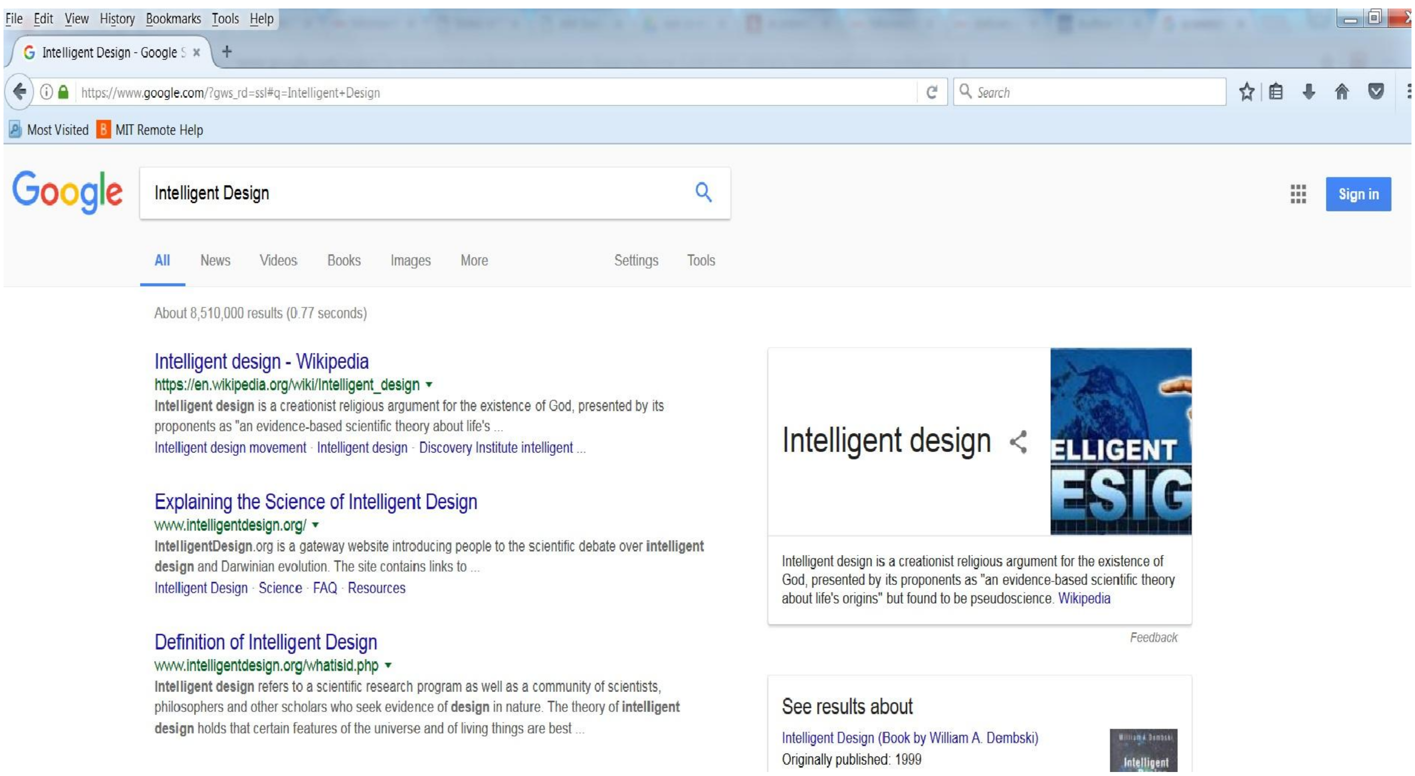
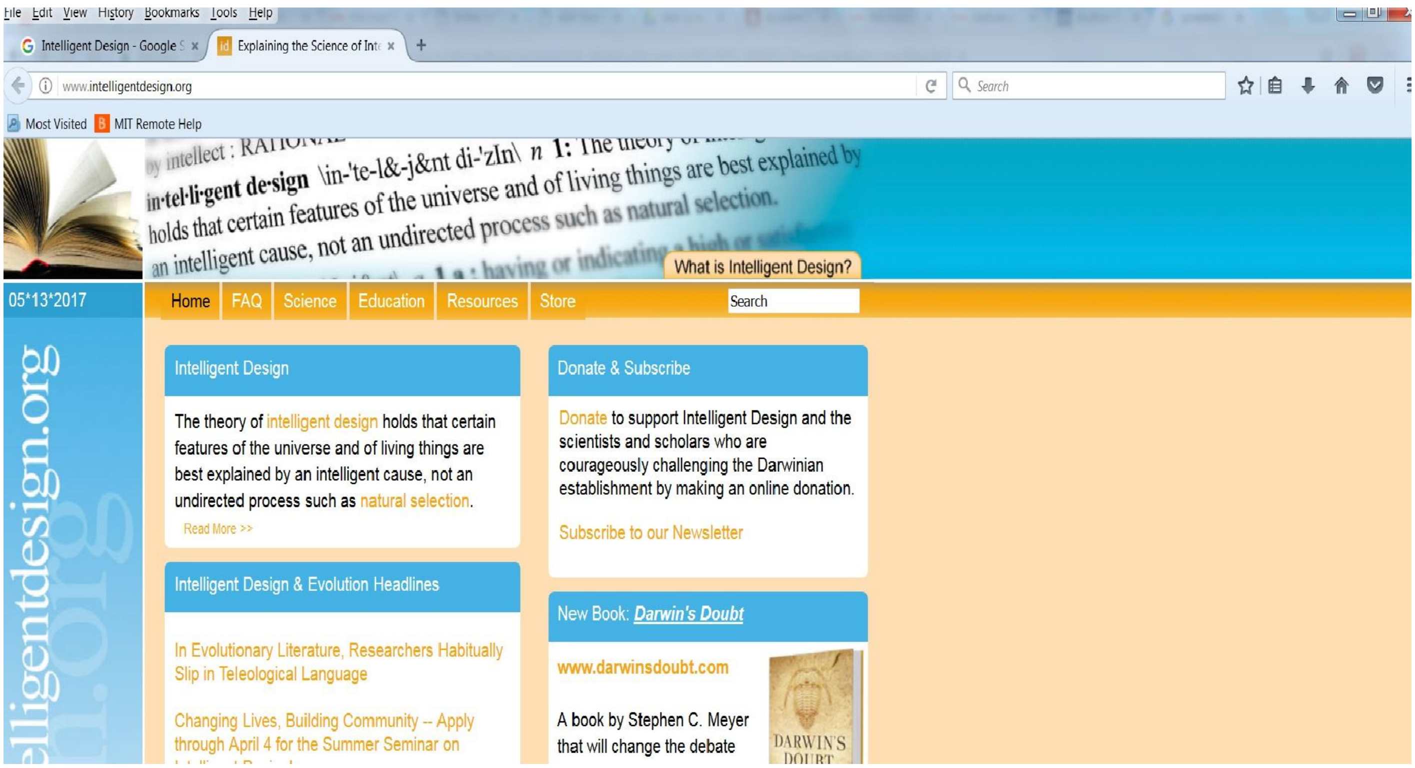


FIGURE 4: WEBSITE FOR 'INTELLIGENT DESIGN'



APPENDIX : SUPPLEMENTARY EVIDENCE

TABLE 14: ROBUSTNESS: ALTERNATIVE CLUSTERING

VARIABLES	Low Educ+High Int (1) ΔScience	Low Educ+Low Int (2) ΔScience	High Educ+High Int (3) ΔScience	High Educ+Low Int (4) ΔScience	Low Educ+High Int (5) ΔScience	Low Educ+Low Int (6) ΔScience	High Educ+High Int (7) ΔScience	High Educ+Low Int (8) ΔScience
Louisiana × After	-0.608***	-0.284	-0.165	0.112	-0.608**	-0.284	-0.165	0.112
	(0.153)	(0.211)	(0.110)	(0.234)	(0.238)	(0.262)	(0.148)	(0.300)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls × Internet	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,972	2,151	2,821	2,180	2,972	2,151	2,821	2,180
R-squared	0.213	0.311	0.267	0.363	0.213	0.311	0.267	0.363

Robust standard errors in parentheses clustered by city in columns (1)-(4) and by state × year in columns (5)-(8). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the change in science test scores. Controls include the number of Internet providers, school district revenue, school district expenditures, child population, proportion of African-Americans, proportion of Whites, average household income, proportion with less than high school degree, proportion with some degree, average ratio of poor income to the average income.