The Impact of 3G Mobile Internet on Educational Outcomes in Brazil*

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Abstract

What is the impact of mobile broadband internet on children's test scores? We compare standardized test scores before and after the staggered entry of 3G into Brazil's 5,570 municipalities using a heterogeneity-robust event study design. We find no effects of mobile internet on test scores for 5th or 9th grade students, and can reject effect sizes of 0.04 standard deviations in both math and Portuguese. Taken together, our results indicate that the arrival of high-speed mobile internet is not sufficient to improve educational outcomes either through direct take-up by individuals or through broader changes to the economy.

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1 Introduction

The number of internet users has increased more than tenfold over the last two decades, from just over 400 million in 2000 to approximately 4.6 billion in 2020 (Roser et al., 2020). In addition to any immediate private benefits and increased social connectedness, this technological revolution generated optimism that digital dividends could drive economic growth and educational opportunity in developing countries (World Bank, 2016). International organizations and national governments alike adopted the cause of universal internet access, including in developing countries such as Brazil, Indonesia, and Nigeria.[1] However, despite this widespread justification for investment in internet infrastructure, there is little evidence to support the claim that internet access will increase educational achievement among students in low- and middle-income countries.

In this paper, we assess the impact of mobile internet coverage on educational outcomes for school students leveraging the staggered roll-out of mobile internet across Brazilian municipalities. We focus on the expansion of the 3G network, the first generation of telecommunications technology that allows users to easily access most features of the internet.[2] Crucially, cellphones are by far the most common and quickly expanding means to access the internet in Brazil and in other developing countries (Bahia and Suardi, 2019), highlighting the importance of understanding how mobile internet affects educational outcomes.

We explore the effect of 3G entry in Portuguese and math test scores using data from over ten years of *Prova Brasil*, a bi-annual standardized exam taken by all students in public schools. Because municipalities which receive 3G in earlier versus later years may have different characteristics in levels, we use event-study research designs to estimate the effects of 3G treatment. First, we estimate robust treatment effects exploiting variation in the timing of 3G coverage from 2008 to 2016 using the methodology proposed by de Chaisemartin and D'Haultfœuille (2020, 2021), which overcomes recently uncovered interpretation challenges of the two-way fixed effects estimates (e.g., Callaway and Sant'Anna, 2020; Abraham and Sun, 2020). Second, we complement this analysis with the standard two-way fixed effects specification.

Our results show that the availability of 3G internet alone does not impact test scores in Portuguese and math in the short- or long-run. We report findings in three steps. First,

[1] One of the United Nations Sustainable Development Goals is to "strive to provide universal and affordable access to the internet in the least developed countries by 2020," and the national governments of emerging and established economies alike (e.g. China and India), are pursuing industrial policies to promote their domestic digital economy.

[2] Roughly speaking, 2G allowed users to send texts, 3G gave access to the internet more broadly, including social media and websites, and 4G allowed users to stream videos (Woyke, 2018).

we show that the arrival of 3G in a municipality, as measured by a carrier first installing an antenna locally, has precisely-estimated zero effects on test scores up to 10 years after entry. In fact, we can reject aggregate effect sizes as small as 0.02 standard deviations in both Portuguese and math test scores.

Second, following a large literature which finds that effects of education interventions may differ by demographic group, we estimate the heterogeneous treatment effects of 3G entry by gender, race, income, and school quality. Mobile internet can enable better access to information and communication, but it could also lead to more distraction and unhealthy content. To the extent that different groups are more or less subject to these forces, effects could differ in important ways. However, we find no important heterogeneity in our estimates.

Third, we show evidence that our null results are not driven by low adoption rates by children or by regions of the country where our treatment variation comes from. In fact, we show that 3G was widely adopted by the Brazilian population during our study period, and that our conclusions hold when restricting attention to a shorter panel with years concentrating higher adoption rates.

In sum, despite the enthusiasm about the potential for internet access to increase educational outcomes in developing countries, this paper shows that the impacts of 3G on test scores in Brazil are very small, if they exist at all. If decisions to support national broadband investments have internalized an expectation of large positive educational impacts, this paper offers a sobering reminder that the provision of technology alone is unlikely to have transformative effects on education, even when considering equilibrium effects and a long time window. Complements built on top of the technology, such as improved teaching practices and educational software may be necessary to reap benefits from the internet (World Bank, 2016). Finally, our results suggest that high-speed internet alone may not compensate for school closures during the COVID-19 pandemic, and that avoiding large declines in educational outcomes will require accompanying policies.

This paper contributes to three strands of literature. First, we contribute to the literature exploring the impact of internet on educational outcomes. To date, the literature has focused mostly on fixed (wired) broadband internet and developed countries (Faber et al., 2015; Fairlie and Robinson, 2013). In contrast, we provide, to the best of our knowledge, the first account of the the impact of *mobile* internet coverage on educational outcomes and the first large-scale evaluation in a developing country. Closely related to our work, Malamud et al. (2019) evaluates the impact of randomly assigned internet-connected laptops to school students in an RCT in Peru and also finds no effects on test scores. Our study differs from it in three important respects: (1) we consider the effects of internet coverage at an aggregate level which incorporates network and general equilibrium effects of internet provision, which are not included in experiments which randomize internet at the student level; (2) we estimate long-run effects, which may be important for the causal channels considered by policymakers who contemplate building internet infrastructure (e.g. changes in the labor market and subsequent reactions in educational investment take several years to emerge); and (3) we focus on mobile internet rather than computer-based internet.[3]

Second, we contribute to previous work on the effects of other ICT technology on education. In the context of developing countries, studies of the One Laptop per Child program in Peru (Beuermann et al., 2015) showed approximately zero effect of computers on test scores. In Romania, the government's initiative to provide computers to low-income households lowered students' grades in school (Malamud and Pop-Eleches, 2011). In both cases, however, there was no significant difference in internet access between treatment and control groups and students used computers mostly for pre-installed applications. Our paper shows that even when high-speed internet is available for a widely used technology (cellphones), the educational benefits are small or inexistent.

Third, we add to the knowledge of the impacts of internet availability on economic development. Hjort and Poulsen (2019) find large positive effects of the arrival of wired broadband internet on employment for both higher and less skilled workers in twelve African countries, but the results of this paper suggest that these labor market gains may not translate into gains in educational achievement. Other studies have focused on the impacts on economic development of alternative ICT technology such as mobile phones, mobile money, and television, and have found that these technologies can increase market efficiency and risk sharing, as well as cause cultural change (Jensen, 2007; Jensen and Oster, 2009; Aker, 2010; Chong et al., 2012; Jack and Suri, 2014). Also in the Brazilian context, Bessone et al. (2020) find that politicians increase their online engagement with voters that gain 3G mobile access but decrease their offline engagement measured by speeches and earmarked transfers towards connected localities where they have a large pre-existing vote share.

The remainder of the paper is organized as follows. In Section 2 we conceptualize the potential effects of mobile internet on education outcomes. We describe the setting in Section 3 and the empirical framework in Section 4. We report and discuss our findings in Section 5. Section 6 concludes with final remarks.

[3]This is an important distinction as individuals in developing countries are more habituated to cellphones rather than computers, which could help them to use mobile internet in a more sophisticated manner for either educational or leisure purposes. Families are also more likely to have multiple cellular devices rather than multiple computers, and the technology is more likely to be used outside of the home.

2 How could internet affect educational outcomes?

Internet may affect children's test scores directly through changes in the time use of children, parents, and teachers. Mobile internet might also induce broader changes in the labor market that indirectly affect children's time use and test scores. For example, firms might restructure to cater to mobile customers, or workers might learn about and apply to jobs online. These changes could affect household income and ultimately children's test scores.

2.1 Direct Effects through Personal Internet Use

The direct impact of internet access depends on the time use changes that it induces in children, parents, and teachers. In areas where internet access is technically available, *affordability* and *interest* are two important considerations for the extensive margin of internet use.

Internet use can be expensive relative to household income, especially in developing countries. Using the internet at all requires buying a device to access the internet (e.g. a smartphone), and continued use requires recurring data plan purchases. If data or smartphone prices are high relative to income, then many people will be conservative with their mobile internet use, even if access is technically available in their region. Thus affordability plays an important role in the impacts of internet access along both the extensive and intensive margins of internet use.

Also, even if internet access is available and affordable, it is possible that people may decide not to use it, perhaps because they do not see any benefit. This may be particularly true in developing countries, as most application and website developers live in high-income countries and make products aimed at users in their own countries. Thus there may be less relevant content for new internet users in developing countries. Low interest in internet access can also be driven by network effects. If few people use the social network and messaging services available through mobile internet, then the benefits of using mobile internet are small, and so low take-up can be self-reinforcing.

Conditional on internet use, the impact of mobile internet depends on what children, parents, and teachers use the internet to do, and on what they substitute away from doing with that time. Fast internet could be a new leisure option which crowds out activities that contribute to student learning, such as homework or lesson preparation. However, internet access could also increase student learning if children substitute time away from playing sports towards reading and writing on social media, or if teachers can more easily find high-quality lesson plans.

2.2 Indirect Effects through the Labor Market

The entry of 3G could also induce changes in the labor market that have indirect effects on children's test scores through employment opportunities and household income. Some jobs may become more demanded, and others less, possibly in a skill-biased way due to the entry of wired broadband internet (Hjort and Poulsen, 2019; Akerman et al., 2015). Or greater importance of online reviews could pick winners and losers, concentrating markets into a smaller number of firms, and possibly increasing monopsony power. On the other hand, easier transfer of information could decrease price dispersion, as Jensen (2007) finds among fisheries in South India after the entry of low speed telecommunications technology. Any of these effects – increased demand for skill, and changes in market power – could change the distribution of firms and returns to education, and consequently affect parents' wages or decisions about children's schooling.

3 Setting: Mobile Internet and Exams in Brazil

Widespread use of mobile internet, combined with low baseline levels of reading and math skills, make Brazil a particularly promising setting to study the impact of internet access on education as a measure of economic development. In discussions of universal internet access as a key to unlock quality education for children in low resource environments, the assumption is often that students have low-quality schooling options and are lacking skills at baseline which may be taught through internet use. International standardized exams from Brazil show that many students are indeed lacking in basic math and reading skills during our time period. In addition, the relatively ubiquitous use of mobile internet in Brazil over our time period makes it likely that mobile internet availability translated into changes in everyday life for most people.

3.1 The Education System in Brazil

Basic education in Brazil can be divided into two stages: elementary school, which is known as "fundamental education," and secondary education, which consists of three additional grades. Elementary school in Brazil is mandatory and includes students from ages 6 through 14. In this study, we focus on students in two years of elementary school: those in grade 5 (age 10) and grade 9 (age 14), the last year of mandatory schooling. Students may attend either public or private schools at the elementary school level. The vast majority (about 80%) of students attend public school. Our study will consider students who attend all public schools which are large enough to have test scores reported in the biennial Prova Brasil (SAEB) standardized exams. Schools are only excluded from the exam if there are fewer than 20 students in either 5th or 9th grade in order to preserve anonymity. Thus the test scores that we consider in our study are representative of a large majority of elementary school students in Brazil.

Educational attainment in Brazil improved rapidly over the early 2000s but has stagnated since 2009. Enrollment increased as basic education become nearly universal, and test scores on the Programme for International Student Assessment (PISA) increased and then plateaued.[4] As of the most recent PISA exam in 2018, which assessed 15-year-old students in reading, mathematics, and science, Brazilian students scored below the OECD average in all subjects. Nearly half (43%) of students scored below the minimum level of proficiency (Level 2) in all three subjects, as compared to the OECD average of 13%.

Brazil's PISA scores in reading and math suggest that a large percentage of students lack basic skills. According to the PISA guidelines, only half of students received at least a Level 2 in proficiency, which means that half of 15-year-old students cannot identify the main idea in a text of moderate length, find information, and reflect on the purpose of a text. The fraction of students scoring below proficient in math was even lower – only 32% of students obtained at least a Level 2 proficiency in mathematics. This means that over two-third of students cannot interpret and recognize how even a simple situation could be represented mathematically. The PISA scores suggest that despite attending a decade of schooling, large fractions of Brazilian students lack basic skills upon graduation from elementary school. The low baseline level of skill that students seem to be learning from their traditional classrooms shows that there is large room for improvement. If internet access is only beneficial to some students whose baseline skills are below a certain level, then this is a promising setting to investigate the potential of internet access to improve student learning.

3.2 Expansion of 3G Internet in Brazil

3.2.1 Why study 3G mobile internet?

"3G" refers to the third generation of wireless mobile telecommunications technology, which greatly increased the capabilities of mobile data transfer, and hence mobile access to the internet. It is the first technology of mobile internet that is considered broadband. In comparison to 2G, the previous technology, the main advantage of 3G is that allows users to use their phones to access websites, to use social media, and to watch videos online (albeit slowly). Under 2G technology, internet functionality was limited to text

[4] See http://www.oecd.org/pisa/publications/PISA2018_CN_BRA.pdf.

messaging and very light web browsing. The next generation (4G), which is not the focus of this paper, allowed users to stream content and participate in video conferences, which was not feasible under 3G. Because the transition from 2G to 3G technology is usually considered the first conversion to mobile broadband, our study focuses on the entry of 3G mobile internet into Brazil.

3.2.2 Institutional background

Large private providers were responsible for the rapid expansion of this 3G network. Their expansion was determined by a combination of commercial interests and coverage requirements imposed by the telecommunications regulatory agency (*Agência Nacional de Telecomunicações*, ANATEL). In 2007, ANATEL auctioned the rights to provide 3G commercially in the whole country to private providers. In this and subsequent auctions, ANATEL imposed requirements that providers also reach sparsely populated regions of the country where the provision of 3G internet would not be economically viable.[5] For example, the company which won an auction to serve the metropolitan region of Sao Paulo (Brazil's richest region) also had to serve the Amazon region (one of Brazil's poorest).

In particular, ANATEL imposed additional targets for the 3G network beyond specific providers. By May 2013, all capitals and cities with populations exceeding 100,000 had to be fully covered by 3G, where full coverage was defined as 80% of the urban areas. Similar targets were set for smaller regions. Of municipalities with between 30,000 and 100,000 inhabitants, 70% of had to be connected by May 2013, and all by June 2016. Even the smallest municipalities had targets set: of municipalities with fewer than 30,000 inhabitants, 20% were supposed to be connected by May 2013, 75% by June 2016, and the rest by December 2019. However, these targets were reached and in fact surpassed. We attempted to explore these population thresholds for identification, but the first stage was too weak for an estimation strategy based on regression discontinuity.

In order to implement these targets in a fair way, ANATEL set up their auction to spread out profitable and remote regions among different providers. Companies were allowed to make a sequential order list of municipalities that they would most to least prefer to connect. Companies then took turns choosing municipalities, in groups of approximately 250 municipalities, until every municipality was selected. Once this assignment was decided, ANATEL and each network provider agreed on dates by which 3G

[5] These requirements were taken seriously: by the end of 2019, the target year for universal 3G access in Brazil, only 0.02% of the population did not have access to 3G. (https://web.archive.org/web/20200531000508/https://olhardigital.com.br/noticia/operadoras-nao-cumprem-meta-e-47-mil-brasileiros-ainda-estao-limitados-a-conexao-2g/98801).

connections would be implemented in each municipality.

3.2.3 Translation of 3G coverage into more widespread use of the internet

3G was introduced in Brazil in 2005, but with limited reach. Starting in late 2007, the territorial reach of the 3G mobile network started to increase more rapidly. From 2008 to 2016, our study period, the share of municipalities with 3G coverage jumped from 5% to 87%, or from 305 to 4831 municipalities (see Figure 1).

This geographic increase in 3G coverage also translated to an increase in mobile internet use. The market share of smartphones, essential for using social media applications which take advantage of the faster data speeds offered by 3G, soared in this time period. In 2011, smartphones made up 13.6% of all cellphone sales, but by 2014 the share of smartphones had increased to 77.5%.[6] In household surveys from 2014, 80.4 percent of households reported that at least one of its members was a mobile Internet user.

While municipality-level data on 3G subscriptions is not available in the study period, Figure 2 shows the evolution of state-level mobile broadband (3G or 4G) penetration between 2010 and 2016. This graph shows the rapid expansion of 3G/4G subscriptions in Brazil. In the 2010 map, all but two states (one of them is Brasilia, the country's very small capital city), had less than 10% of the population subscribing to 3G/4G services. In 2012, only two years later, all municipalities had between 10% and 50% 3G/4G penetration. By the end of our sample period in 2016, all municipalities had 3G/4G penetration levels of at least 50%, with most having over 70% penetration. Overall, as shown in Appendix Figure A.2, from 2009 to 2017 the number of subscriptions jumped for 2 to 88 per 100 inhabitants, reaching over 50% of the population by 2014.[7]

Because mobile is usually the primary – and often only – means to access the internet in Brazil and other low- and middle-income countries, the increase in mobile internet use indicates an increase in *any* internet use. In 2014, Brazil had 134 mobile phone subscriptions per 100 inhabitants, and only 10.5 fixed broadband Internet subscriptions per 100 inhabitants (World Bank).

To formalize the relationship between municipality 3G coverage and mobile broad-

[6]Data from current and previous versions of this Teleco page (https://www.teleco.com.br/smartphone.asp), accessed through the Wayback Machine.

[7]This is not surprising. Brazil is known as one of the most active countries in the Internet (See `https://www.statista.com/topics/2045/internet-usage-in-brazil/`). Since the privatization in the 90s, the telecommunication sector is considered efficient and competitive (See `https://www.anatel.gov.br/dados/relatorios-de-acompanhamento/`). Because of that, the price of Internet data is relatively cheap in the country (See `https://www.cable.co.uk/mobiles/worldwide-data-pricing/`). Moreover, halfway through our sample period, smartphones dominated the cellphone market, allowing users to use 3G technology.

band subscriptions, we create a variable capturing the share of population covered according to our measure of coverage in the DDD region level. [8] In Figure 3, we correlate this variable with the share of subscriptions in the DDD region by year. Although we cannot interpret the evidence causally, the figure suggests that in the beginning of our sample period, coverage is associated with a modest increase in subscriptions. A 1 percentage point (p.p.) increase in the population treated increases subscriptions by a mere 0.03 p.p. However, this relationship is strongly increasing over time. Between 2014 and 2016, subscriptions increase by .61 p.p. to .77 p.p. when an additional 1 p.p. of the population is treated. Importantly, this is likely a lower bound since when we construct the share of population covered, we assume that all areas in the municipality are treated, which is unlikely to be true.

4 Empirical Framework

4.1 Data

Education. The main educational outcome in this paper is exam scores from the Prova Brasil, a nation-wide, standardized exam administered every other year to all 5th and 9th grade students in Brazilian public schools that have at least 20 students enrolled in those grade levels. We use Prova Brasil test scores and survey responses from 2007, 2009, 2011, 2013, 2015, and 2017 to assess the effects of 3G. The anonymized student-level data are publicly available through the *Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira* (Inep).[9]

For each student in 5th and 9th grade, we estimate the impact of 3G on their Portuguese language and math test scores. We use the exam score standardization provided by INEP, which standardizes the scores against a 1997 exam. When students take the exam, all students, the proctoring teachers, and the headmaster of the school complete a survey. We use the student surveys to obtain demographic characteristics of students (race, gender, and family background), which we use as controls in some specifications.

Internet. The date that 3G enters a municipality is defined as the year in which the first operator started to offer 3G commercially for consumers in that municipality. These data are obtained from Teleco, a telecommunications consultancy firm in Brazil, that gathers the information from all cellphone operators in the country. For our analysis, we consider

[8] We create this variable in the DDD level because it is the most disaggregated information available in the period about cellphone subscriptions. There are 67 DDD regions in the country, each of which is a subset of a Brazilian state.

[9] Source: https://www.gov.br/inep/pt-br/acesso-a-informacao/dados-abertos/microdados.

a municipality to be treated with 3G in year t if 3G started operating in that municipality by October (inclusive) of year t. Because the Prova Brasil exam takes place in November, if a municipality received 3G in November or December of year t, then we consider that municipality to be treated in year $t + 1$.

We gather data about the number of mobile internet subscriptions by municipality-year for all technologies (2G, 3G and 4G) between 2008 and 2016 from National Telecommunications Agency (ANATEL).

Kids Internet Usage. We collect data about the patterns of internet usage by kids aged 9 to 17 from the TIC Kids Online survey between 2015 and 2018 from the *Centro Regional de Estudos para o Desenvolvimento da Sociedade da Informação* (CETIC). The survey includes information about usage profiles, activities done online, social media, internet usage skills, mediation by parents, consumption, risks and damage. Because of small sample sizes and regulations regarding privacy, the data are only available at the region level (i.e., North, Northeast, Center-West, Southeast and South).

Other data sources. We complement our data analysis with the following sources from Brazilian government agencies. We have data about (i) municipality GDP and population from the Brazilian Institute of Geography and Statistics (IBGE) for 2002-2017, and (ii) municipality socioeconomic characteristics from the 2000 and 2010 Censuses.

4.2 Empirical Strategy: Robust Difference-in-Differences

A series of recent papers demonstrate that the commonly-used two-way fixed effects model has undesirable properties when treatment effects are heterogeneous (de Chaisemartin and D'Haultfœuille, 2020; Callaway and Sant'Anna, 2020; Abraham and Sun, 2020; Goodman-Bacon, 2020). In particular, if treatment effects are heterogeneous by treatment cohort, then the overall estimated treatment effect can be a non-convex combination of different conditional average treatment effects, with some treatment effects receiving negative weights (Abraham and Sun, 2020). Under this condition, the interpretation of the coefficients in the two-way fixed effects model is not economically meaningful. It is possible that all dynamic treatment effects are positive, while the estimated aggregate treatment effect is negative (Borusyak and Jaravel, 2017). Given that the effects of 3G mobile internet are likely to have changed over time as complementary technology developed, the treatment effects in our setting are likely to be heterogeneous by treatment cohort. In order to uncover unbiased estimates of treatment effects even when treatment effects may vary by cohort, we employ the estimators proposed in de Chaisemartin and D'Haultfœuille (2020, 2021).

4.2.1 Empirical Specification

Let the number of treatment cohorts be denoted by G, with cohorts indexed by $g \in \{1, ..., G\}$. In this setting, $G = 9$ because municipalities in our sample are treated in years in the interval of 2008 to 2016. Let T be the number of time periods, with time periods indexed by $t \in \{1, ..., T\}$. In this setting, $T = 6$ because the Prova Brasil exams take place every odd year from 2007 to 2017.

Let $D_{m,g,t}$ denote the treatment status of municipality m in treatment group g at period t, with $\Delta D_{m,g,t} = D_{m,g,t} - D_{m,g,t-1}$. Let $Y_{m,g,t}(\mathbf{D})$ denoting the potential outcome (i.e. average test score) of municipality m in treatment group g at period t, if the treatment status of municipality m follows the time path of vector $\mathbf{D}$ from period 1 to period T. Note that this implies that the potential outcome of municipality m at time period t may depend on its treatment status in earlier and later periods, which allows for dynamic treatment effects in which 3G coverage at an earlier time period affects test scores in a later time period.

First define $DID_{+,t,l}$ as the difference-in-differences estimator which estimates the effect of treatment by comparing groups which became treated at time period $t - l$ to groups which are untreated from period 1 to t. This can be estimated as $DID_{+,t,l} = \sum_{g:\Delta D_{m,g,t-l}=1} \frac{N_{m,g,t}}{N_{t-l}} (Y_{m,g,t} - Y_{m,g,t-l-1}) - \sum_{g:\Delta D_{m,g,\tau}=0 \forall \tau <= t} \frac{N_{m,g,t}}{N_t^{nt}} (Y_{g,t} - Y_{g,t-l-1})$, where $N_{t,l}$ is the number of students in municipalities treated at time period $t - l$, and N_t^{nt} is the number of students in municipalities which have not been treated by time period t. Under the assumptions below, $DID_{+,t,l}$ it is an unbiased estimator of the treatment effect l periods after the start of treatment (i.e. the effect of having been treated for $l + 1$ time periods).

Second we construct $DID_{+,l}$ as a weighted average of the difference-in-differences estimators which estimate the effect of treatment after l time periods for particular cohorts $DID_{+,t,l}$. This estimator $DID_{+,l}$ is an unbiased estimator of the average effect of the arrival of 3G mobile internet l years ago, and is defined as $DID_{+,l} = \frac{\sum_{t=l+2}^{NT} N_{t,l} DID_{+,t,l}}{\sum_{t=l+2}^{NT} N_{t,l}}$.

4.2.2 Assumptions

This empirical strategy requires several assumptions. One is that there is no anticipation; that is, the average test score in a municipality does not depend on its treatment status in future time periods. This assumption seems likely to hold, as students were unlikely to know the exact roll out date of 3G in their area, and even if they were to know, it seems implausible that they would take into account future 3G coverage in their academic efforts. Formally, this method requires that for all g and for all $\mathbf{D}$, $Y_{g,t}(\mathbf{D}) = Y_{g,t}(d_1, ..., d_t)$.

A second necessary assumption is related to independence and exogeneity of treatment and potential outcomes. Conditional on whether or not a group has 3G coverage, the shocks affecting its potential outcomes must be mean independent of whether other groups have 3G coverage. This condition is satisfied if the potential test scores and 3G coverage status of different municipalities are independent from each other. This seems likely to hold, as we expect a municipality's test scores to depend only on whether that municipality has 3G coverage (and not whether other municipalities also do or do not have 3G coverage). This method also requires exogeneity; that is, shocks affecting a group's potential outcomes should be mean independent of group g's treatment status. Because the roll-out of 3G was not determined by any shocks to municipalities' test scores or economic conditions, the exogeneity assumption seems plausible in this context.

Lastly, this method requires the standard parallel trends assumption common to DID models. In every treatment cohort, the expectation of the never-treated test scores must follow the same evolution over time conditional on our control variables. Formally, for all $t \geq 2$, it must be that $\mathbb{E}[Y_{g,t}(\mathbf{1}) - Y_{g,t-1}(\mathbf{1})]$ is the same across all g.

4.3 Benchmark two-way fixed effects (TWFE)

To complement our empirical strategy from Section 4.2.1, we also estimate the effect of mobile internet on test scores using the benchmark two-way fixed effects specification:

$$y_{mt} = \sum_{e=-4}^{5} \beta_e z_{m,t+e} + \delta_m + \alpha_{s(m)t} + \varepsilon_{mt} \tag{1}$$

$$y_{mt} = \beta_{agg} z_{m,t} + \delta_m + \alpha_{s(m)t} + \epsilon_{mt} \tag{2}$$

where y_{mt} is the average test score in municipality m during year t. We estimate the model separately by math and Portuguese test scores, and both aggregating and separating the two grades. $z_{m,t+e}$ is a dummy variable equal to one when municipality m received 3G in relative year e. Since the exam happens every two years in November, we define that the unit receives treatment at t if they were treated at some point between November of year $t-1$ and October of year t. We always control for municipality δ_m and state-by-year $\alpha_{s(m)t}$ fixed effects. We cluster standard errors at the municipality level, which is the unit of treatment (Abadie et al., 2017).

The coefficients of interest in Equations (1) and (2) are β_e, which trace the time path of treatment effect on test scores at *event time e*, i.e., e years after 3G entry, and β_{agg}, which captures the average effect post treatment. For $e < 0$, β_e captures pre-treatment trends, which serve as a test for identification, as discussed below. In our benchmark specification, we weigh the observations by the number of students that took the exam in each year, municipality, exam type, and grade. Thus, our treatment should be interpreted as the average treatment effect across students. Finally, we normalize $\beta_{-1} = 0$, so estimates should be interpreted relatively to the excluded time period, as it is standard in difference-in-differences design.

The requirement for identification of the causal effect of 3G entry on test scores is that municipalities receiving 3G at different years were on parallel trends in test scores prior to the arrival of 3G and did not change trends, for reasons other than treatment, after 3G was deployed. The always- and never-treated municipalities, those that were already treated at the beginning (2008) or that were still not treated at the end (2016) of our sample period, seem to be on different pre-treatment trends, so we exclude them from the analysis. In contrast, we confirm in Section 5 that the complier municipalities were on parallel trends with respect to test scores before treatment, giving credence to this empirical strategy.

5 Results

5.1 Robust difference-in-differences estimator results

Table 2 and Figure 5 report the dynamic effects of 3G mobile internet on test scores using the robust difference-in-differences estimator proposed in de Chaisemartin and D'Haultfœuille (2020, 2021) and described in Section 4.2.1. These estimates are valid even if the treatment effect of 3G mobile internet is heterogeneous across municipalities, in contrast to the more commonly used two-way fixed effects event study regression, which we also estimate and report results from in Section 4.3. We can rule out very small effect sizes of about 0.02 standard deviations in Portuguese, and 0.01 standard deviations in math within two years of treatment when pooling 5th and 9th grade students. Even 8 years after the entry of 3G, for which we have less precise estimates because we have fewer observations to estimate effects from, we can rule out effect sizes of about 0.04 standard deviations in Portuguese and 0.05 standard deviations in math. Results are qualitatively the same in unweighted regressions reported in Appendix Table A.1 and Figure A.3.

Disaggregating by grade, we potentially lose some precision but can also rule out small effects of 3G on test scores. For 5th grade students, we can rule out effect sizes of 0.02 standard deviations in Portuguese and 0.014 standard deviations in math in the two years following treatment. For 9th grade students, we can rule out effect sizes of 0.015 standard deviations in Portuguese and 0.015 standard deviations in math in the two years following treatment.

We examine whether these null effects could be driven by countervailing heterogeneous effects which are similar in magnitude. As it is common for educational interventions to have differential effects across demographic and socioeconomic groups, we examine whether mobile internet has differential effects on test scores by student gender, race, wealth, and school quality. As students from higher wealth families or better schools are more likely to have access to a smartphone, we expect any effects of mobile internet to be larger for these subgroups.

We report results for gender in Figure 6, race in Figure 7, income in Figure 8, dividing the sample into families being above and below the municipality's median income, and baseline school quality in Figure 9, dividing the sample into schools being above and below the municipality's median school test scores. We do not find evidence of heterogeneous effects along any of these axes which could cancel each other out to produce our null result. The figures offer similar amounts of precision compared to the average results above, still allowing us to exclude effects of even 0.04 SD's in math and Portuguese up to four years after entry. To put this in perspective, in Brazil, Varjão (2019) finds that local radios increase test scores by 0.09 SD's, and Akhtari et al. (2020) find that bureaucrat turnover reduces test scores by 0.05-0.08 SD's using data from the same national exam.

5.2 Benchmark two-way fixed effects model

Appendix Table A.2 and Figure A.4 report the results of the event study estimated using the benchmark two-way fixed effects (TWFE) model described in Section 4.3. The estimates show that there are no effects of 3G mobile internet on test scores. This zero effect holds true for both Portuguese and math, in both 5th and 9th grades. The pre-event time dummies show that there are no discernible trends in test scores leading up to the entry of 3G. Thus, despite the differences in observable characteristics between municipalities which received 3G earlier versus later in our sample period (summarized in Table 1) and in line with our findings in Section 5.1, the event study estimation offers reassuring evidence that test score trends for municipalities which received 3G earlier rather than later would have proceeded in parallel in the absence of treatment.

The estimated effects on test scores are very close to zero throughout the 8 to 10 years after network providers begin offering 3G in the municipality. The largest estimated effect is 0.04 SD's at the 8-10 year event time for 5th grade Portuguese, and this estimate is imprecisely estimated and statistically indistinguishable from zero. For Portuguese, the event study shows a slight (insignificant) positive trend for 5th grade, and a slight negative trend for 9th grade. In math, the event study shows no discernable trend for 5th grade, and a slight negative trend for 9th grade. Other than 9th grade scores in event time 4-6 years after the entry of 3G, all estimates for each combination of 5th grade, 9th grade, Portuguese, and math are indistinguishable from zero at the 95% level with standard errors clustered at the municipality level.

In the last row of Appendix Table A.2, we pool the dynamic treatment effects from Equation (1) into a single estimate. The estimates from this exercise never exceed even 0.013 standard deviations from zero in any specification. However, we find that these aggregated effects are not a convex combination of the estimated dynamic treatment effects. As discussed in Section 4.2, recent papers in econometrics show that aggregating dynamic effects in a TWFE model can result in nonsensical aggregate estimates which place negative weights on the dynamic effects. Our estimates provide a real-world example of this failure of the TWFE models.

5.3 Why doesn't 3G affect educational outcomes?

We interpret our results as evidence that the expansion of 3G internet usage in Brazil had no effects on educational outcomes. In Section 3.2.3 we argue that 3G coverage did lead to greater internet use, and in Section 5.1 we show that it had a precisely zero effect on test scores. However, even if 3G coverage did translate into greater use of mobile internet at the municipality level in Brazil and if mobile internet has a non-zero effect on test scores, there are at least two alternative reasons why we might find no effects of 3G coverage on educational outcomes. In this section, we explore the following alternative explanations for our empirical results: (1) adults access mobile internet, but children do not; (2) in early years, adoption rates were too low for us to detect effects on the population average.

Children's access to mobile internet

One concern might be that although internet access increased over our study period, internet use was concentrated among adults, and children were largely unable to access the internet. However, representative national surveys conducted by the Regional Center for Studies on the Development of the Information Society (CETIC), a department of the Brazilian Network Information Center (NIC.br), suggest that mobile internet coverage extended internet use to children and adolescents as well.

In the y-axis of Figure 4, we show the share of kids and adolescents using the internet in each of the five regions in Brazil. In the x-axis, we show the share of of municipalities with 3G in the region according to our measure of entry described in Section 4.1. In 2015, the earliest survey which asked this question, at least 54% and 70% of the kids in the North and Northeast regions, the poorest in the country, used internet in the past 30 days. In the richest regions, the usage varied between 80% and 90%. One limitation is that this survey does not distinguish between mobile and computer-based internet. However, we at least see a positive correlation between 3G expansion and internet usage for all but one region in the country, suggesting that our measure of coverage affects high-speed internet usage by kids and adolescents.

Low 3G adoption rates in early years of study period

Even though 3G coverage and access increases throughout the entire study period (2008-2016), adoption only crosses the 50% mark and rapidly increases to over 80% of the population after 2014 (see Figure A.2). Moreover, our data sets, which describe high rates of mobile internet use among children and adolescents, only begin in 2015. Thus, perhaps one of the reasons we find no effect of 3G is because our empirical strategy aggregates effects of 3G over multiple years in which the usage of 3G was modest and, thus, attenuates the estimated effects to zero. To address this possibility, we estimate the short-term effects of 3G with the estimator proposed by de Chaisemartin and D'Haultfœuille (2020, 2021) but restricting observations only to years 2013 and 2015.

In Table 3 we conclude that it is not the case that relatively low internet use in early sample years are driving the null results: the effect of 3G is zero for both Portuguese and math, be it aggregating grades in Columns (1) and (2), or distinguishing between 5th and 9th grades in Columns (3)-(6).

Discussion

In summary, we find that 3G coverage translates into 3G usage, and that most kids and adolescents use broadband internet, at least by the end of our sample period. Importantly, other papers in the literature have found positive effects of broadband internet in other outcomes with similar or smaller levels of penetrations. In the same setting as ours, Bessone et al. (2020) find that politicians react to the expansion of 3G internet by mentioning the municipalities more often on Facebook, while transferring fewer Federal resources to them. In Nigeria and Senegal, in spite of much smaller internet usage, Bahia et al. (2020) and Masaki et al. (2020) respectively, both find that consumption increases and extreme poverty decreases when a household is covered by the 3G network. Finally, Hjort and Poulsen (2019) find that access to high-speed (fixed) internet increases employment in Africa, although only 20% of individuals in the countries they have data for report using internet weekly.

6 Conclusion

This paper studies the effects of access to 3G mobile internet on educational outcomes for children in Brazil. We exploit the staggered introduction of 3G technology across municipalities to estimate the impacts of mobile internet using difference-in-differences regressions. Across all our measures of interest we find precisely estimated null effects.

Ex ante, provision of 3G internet could impact education through a variety of channels, making the net effect an empirical question. On the one hand, mobile internet could directly affect children's time use, allowing them to practice basic reading and writing skills, as well as increasing the private returns to those skills. At a more aggregate level, if the arrival of mobile internet in Brazil has similarly positive effects on employment as it did in the twelve countries in Africa studied by Hjort and Poulsen (2019), then effects through parents' labor market outcomes could also raise test scores. Additionally, if mobile internet is a skill-biased technology, as has been found with computer-based wired internet access (Akerman et al., 2015; Hjort and Poulsen, 2019), then the entry of mobile internet might incentivize greater educational investment through increased returns to education. On the other hand, mobile internet might crowd out study time in favor of games, social media, and other leisure activities. In recent years, the focus of news articles (at least in high income countries) has been the negative effects of mobile internet use on child and teenager psychology.[10] Because the results of these changes may take several years to emerge, and because they rely on the network effects of society-level internet adoption, we study the dynamic effects of mobile internet over a decade and at an aggregate level of treatment. We find that despite high take up of 3G technology over our sample period, the effects of mobile internet on educational outcomes are precisely zero.

Based on our initial findings, we see a variety of avenues for future research. If access to fast mobile internet is just a necessary but not sufficient condition for improvements in education, then it is crucial to understand whether complementing analog policies can be the missing link. In the mean time, neither pure optimism viewing mobile internet as a transformative driving force in education for children and teenagers or pessimism viewing it as a cause for major concern were entirely justified.

[10] A couple examples (of many): "A Dark Consensus About Screens and Kids Begins to Emerge in Silicon Valley" (NYTimes, 2018); "Dr. Siegel: Screen time is doing serious harm to our teens" (Fox News, 2018).

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Tables

Table 1: Municipality Characteristics by 3G Adoption Year

Year of 3G Adoption	Number of Municipalities	Income Per Capita	Electricity (%)	Urban (%)	Portuguese Score	Math Score
2008	118	327.55	0.97	0.91	-0.82	-0.51
2009	638	223.74	0.94	0.78	-0.98	-0.68
2010	682	200.28	0.93	0.66	-0.96	-0.64
2011	1495	193.09	0.89	0.66	-0.95	-0.63
2012	2561	178.55	0.87	0.6	-0.97	-0.63
2013	695	138.56	0.8	0.57	-1.14	-0.82
2014	634	134.62	0.86	0.58	-1.13	-0.81
2015	900	135.61	0.84	0.51	-1.1	-0.76
2016	1050	117.04	0.75	0.49	-1.19	-0.88
>2016	1347	116.89	0.76	0.5	-1.17	-0.85

Note: Descriptive statistics of the municipalities by the year in which they received 3G. ">2016" refers to the subsample of municipalities that gained 3G access in November 2016 or later. These municipalities are excluded from our event study analysis. "Income per capita" is in Brazilian Reals, and comes from the 2000 census. Rates of electricity access and urbanity are also from the 2000 census. The test scores in Portuguese and math are average scores on the 2007 Prova Brasil giving equal weight to each student.

Table 2: Effects of 3G on Students Test Scores

	All grades		5th grade		9th grade	
	Portuguese	Math	Portuguese	Math	Portuguese	Math
	(1)	(2)	(3)	(5)	(6)	(8)
6-8 years before	-0.004	-0.016	-0.005	-0.015	0.003	-0.013
	(0.016)	(0.018)	(0.016)	(0.019)	(0.015)	(0.019)
	[0.788]	[0.360]	[0.763]	[0.436]	[0.836]	[0.494]
4-6 years before	-0.012	-0.009	-0.011	-0.012	-0.006	-0.004
	(0.008)	(0.009)	(0.009)	(0.011)	(0.010)	(0.009)
	[0.164]	[0.311]	[0.211]	[0.291]	[0.545]	[0.673]
2-4 years before	-0.001	-0.002	-0.005	-0.008	0.003	0.003
	(0.006)	(0.006)	(0.006)	(0.009)	(0.006)	(0.006)
	[0.904]	[0.788]	[0.458]	[0.341]	[0.607]	[0.647]
0-2 years after	0.009	0.003	0.008	0.000	-0.005	-0.005
	(0.005)	(0.005)	(0.005)	(0.007)	(0.005)	(0.005)
	[0.056]	[0.513]	[0.117]	[0.943]	[0.310]	[0.314]
2-4 years after	0.027	0.013	0.012	0.002	0.011	-0.003
	(0.008)	(0.009)	(0.009)	(0.010)	(0.009)	(0.008)
	[0.001]	[0.121]	[0.184]	[0.826]	[0.238]	[0.735]
4-6 years after	0.007	-0.001	-0.002	-0.021	-0.022	-0.009
	(0.012)	(0.014)	(0.019)	(0.025)	(0.022)	(0.018)
	[0.552]	[0.952]	[0.926]	[0.393]	[0.306]	[0.634]
6-8 years after	0.008	-0.021	0.018	-0.044	-0.048	-0.039
	(0.018)	(0.036)	(0.040)	(0.071)	(0.051)	(0.027)
	[0.653]	[0.572]	[0.656]	[0.540]	[0.341]	[0.142]

Note: This table shows the estimates from the robust differences-in-differences estimator (de Chaisemartin and D'Haultfœuille, 2020) discussed in Section 5.1. Standard errors clustered at the municipality level are presented under ( ). P-values are presented under [ ].

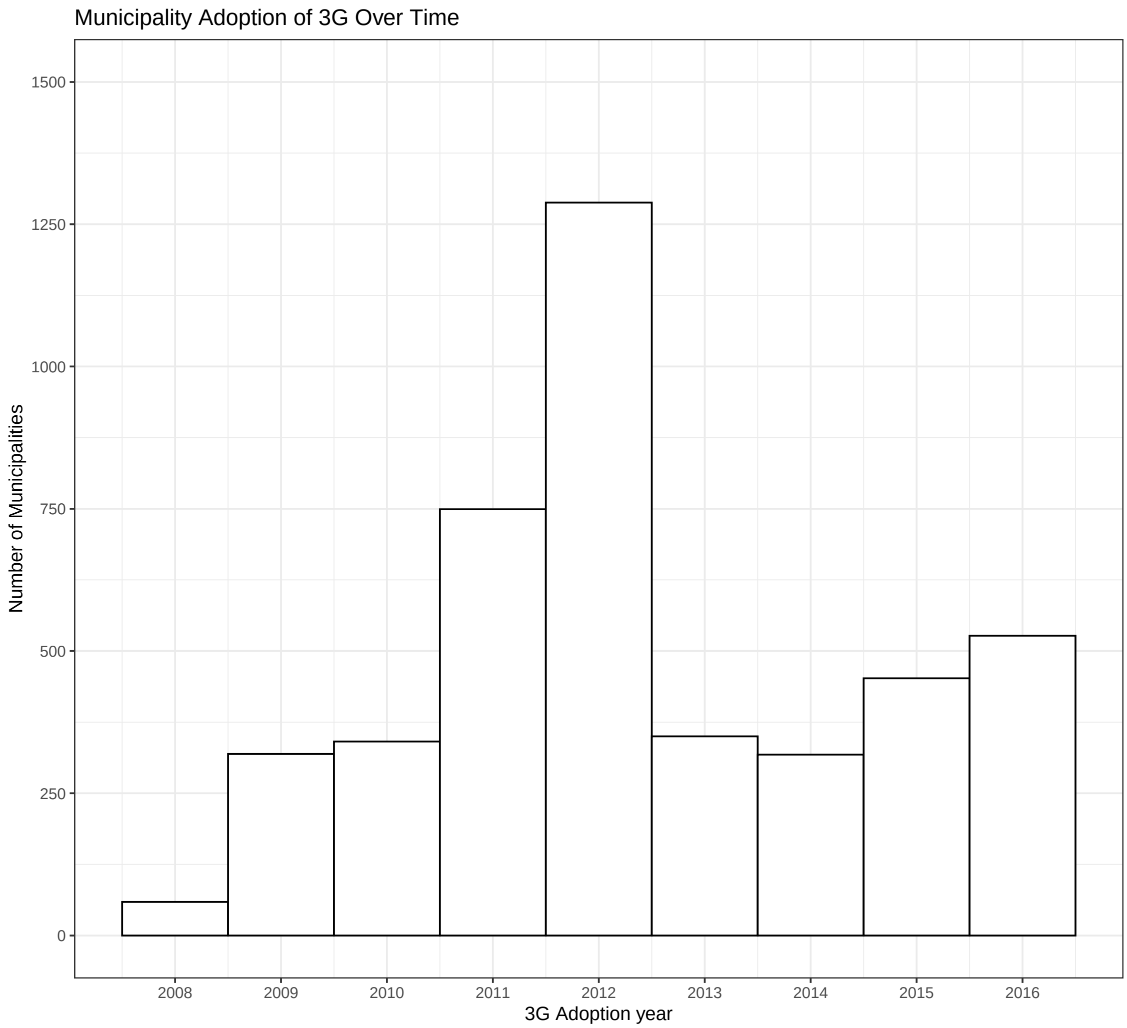
Table 3: Instantaneous Effect of 3G on Students Test Scores - Later Years

	All grades		5th grade		9th grade	
	Portuguese	Math	Portuguese	Math	Portuguese	Math
	(1)	(2)	(3)	(4)	(5)	(6)
Instantaneous	0.024	0.002	0.020	-0.011	0.001	-0.001
Effect	(0.017)	(0.016)	(0.018)	(0.021)	(0.016)	(0.016)
	[0.151]	[0.892]	[0.266]	[0.609]	[0.969]	[0.934]

Note: This table shows the estimates from the robust differences-in-differences estimator (de Chaisemartin and D'Haultfœuille, 2020) discussed in Section 5.3. We include only the exams from 2013 and 2015 in the sample. The point-estimates represent the impact of 3G adoption within 2 years of adoption. Standard errors clustered at the municipality level are presented under ( ). P-values are presented under [ ].

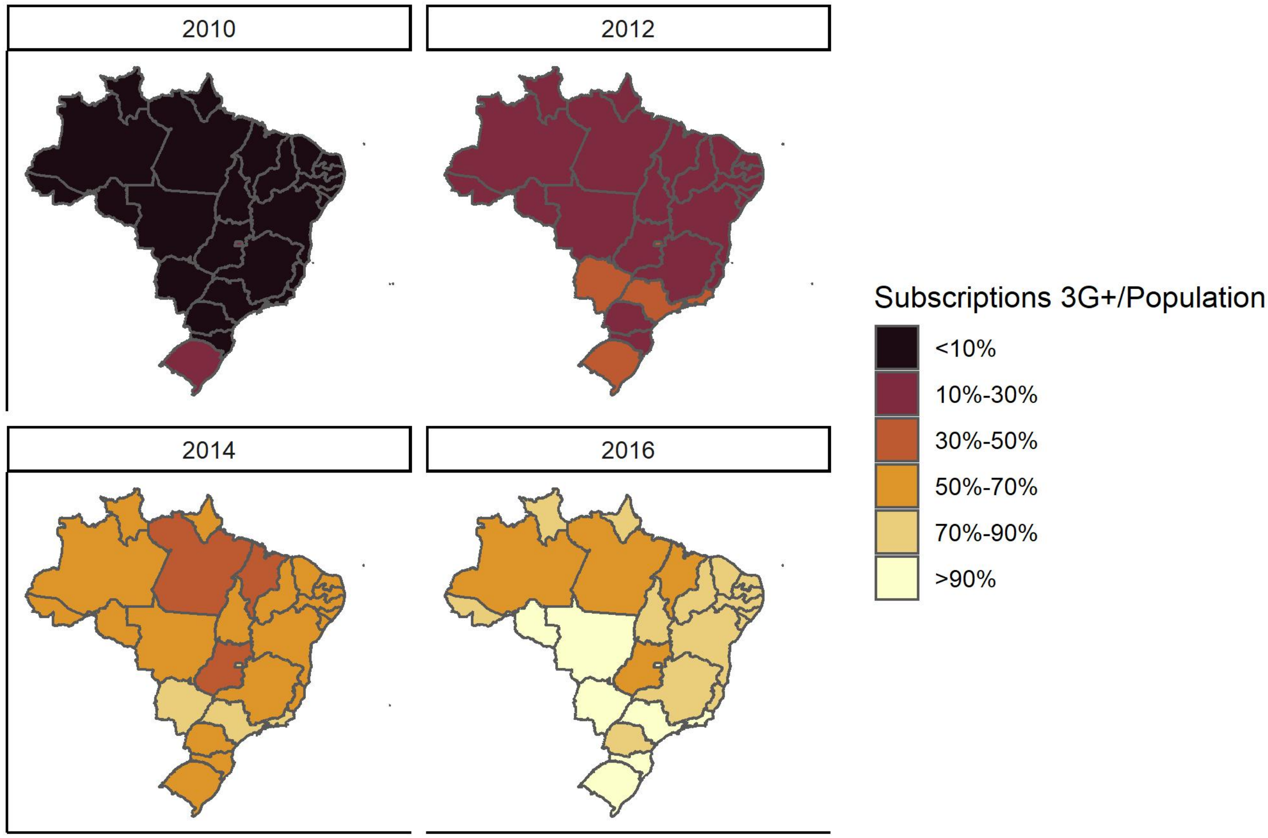
Figures

Figure 1: Municipality Adoption of 3G Over Time



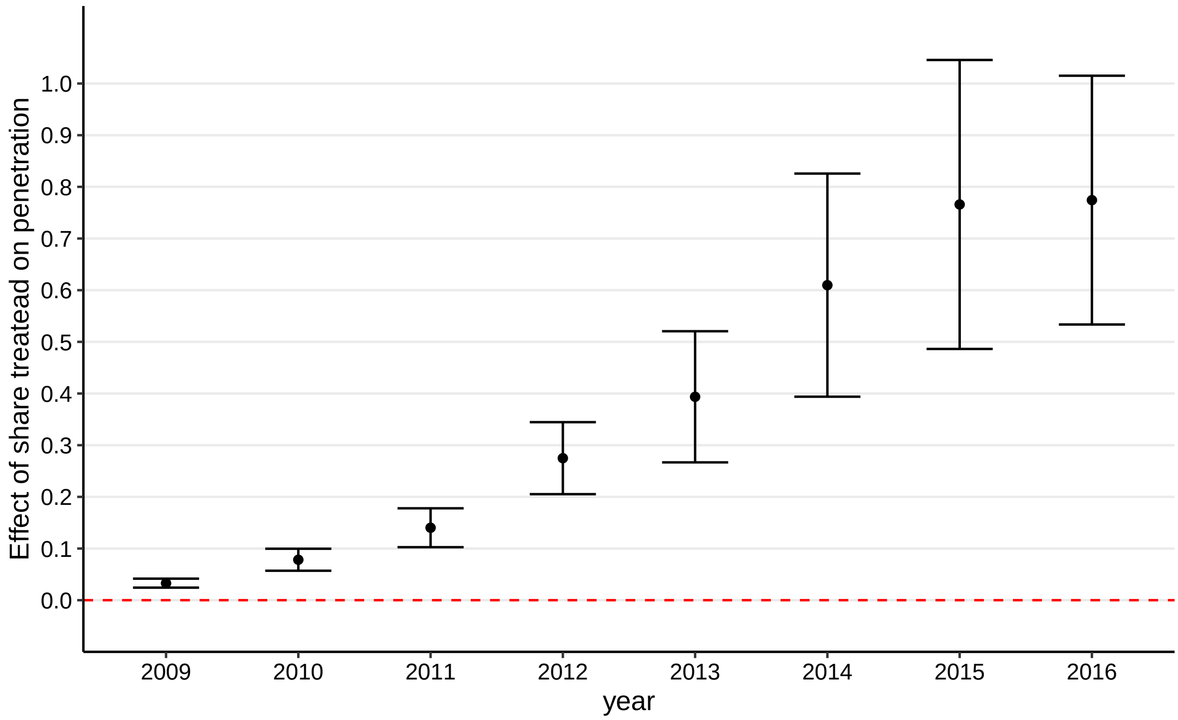
Note: This histogram displays the timing of 3G entry in our municipality study sample. There are 4403 municipalities included in this histogram, which is composed of municipalities that network providers entered between 2008 and 2016. At the beginning of our sample period in 2008, only 305 municipalities ($\approx$ 5%) already had 3G coverage. By the end of our study sample in 2016, 4831 municipalities ($\approx$ 87%) had 3G coverage. A municipality is considered to be treated in year t if the network provider reports upgrading to 3G coverage in January through October of year t, and considered to be treated in year $t + 1$ if the upgrade occurs in November or December. This definition is chosen to match the Prova Brasil exam schedule, which is administered in November.

Figure 2: Evolution of 3G usage by state



Note: Each of these maps show the number of mobile broadband internet (3G or 4G) subscriptions in the state level between 2010 and 2014. Subscriptions are measured as the number of devices with access to either 3G or 4G internet plans (ANATEL). Darker colors indicate *less* penetration of 3G internet in the State. This graph shows that in 2010, all but 2 states had less than 10% of the population subscribing to 3G/4G services. In 2016 in contrast, all municipalities had at least 50% of penetration.

Figure 3: 3G Coverage and Number of 3G Subscribers

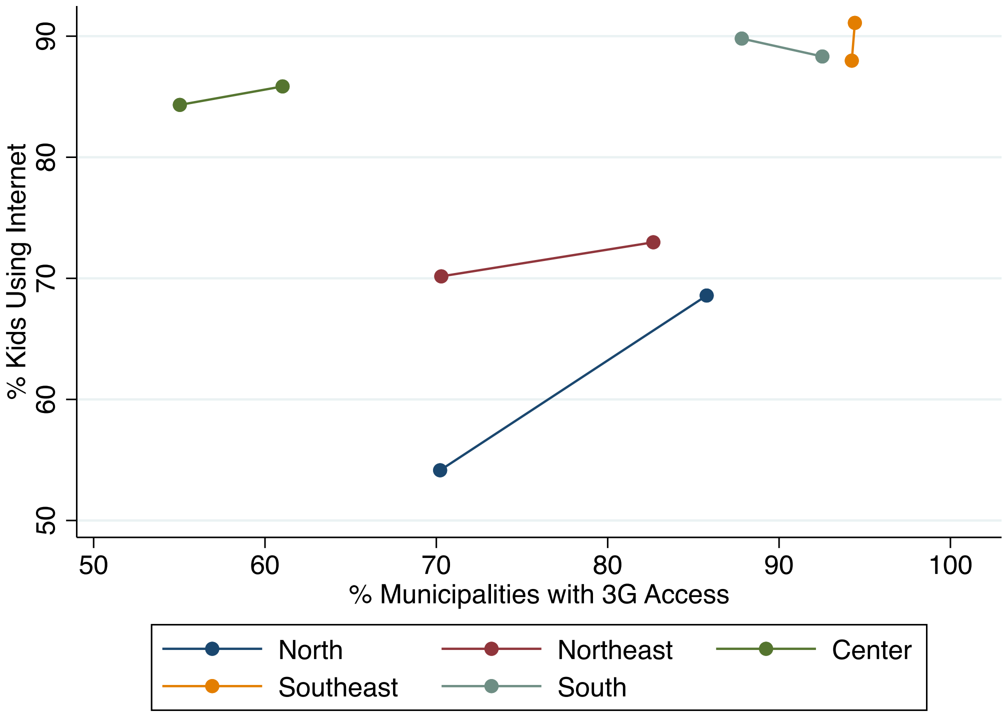


Note: The dots show the β_t estimates in the regression

$$\text{penetration}_{it} = \sum_{t'=2009}^{2016} \beta_{t'} \text{share population treated}_{it} + \delta_t + \varepsilon_{it}$$

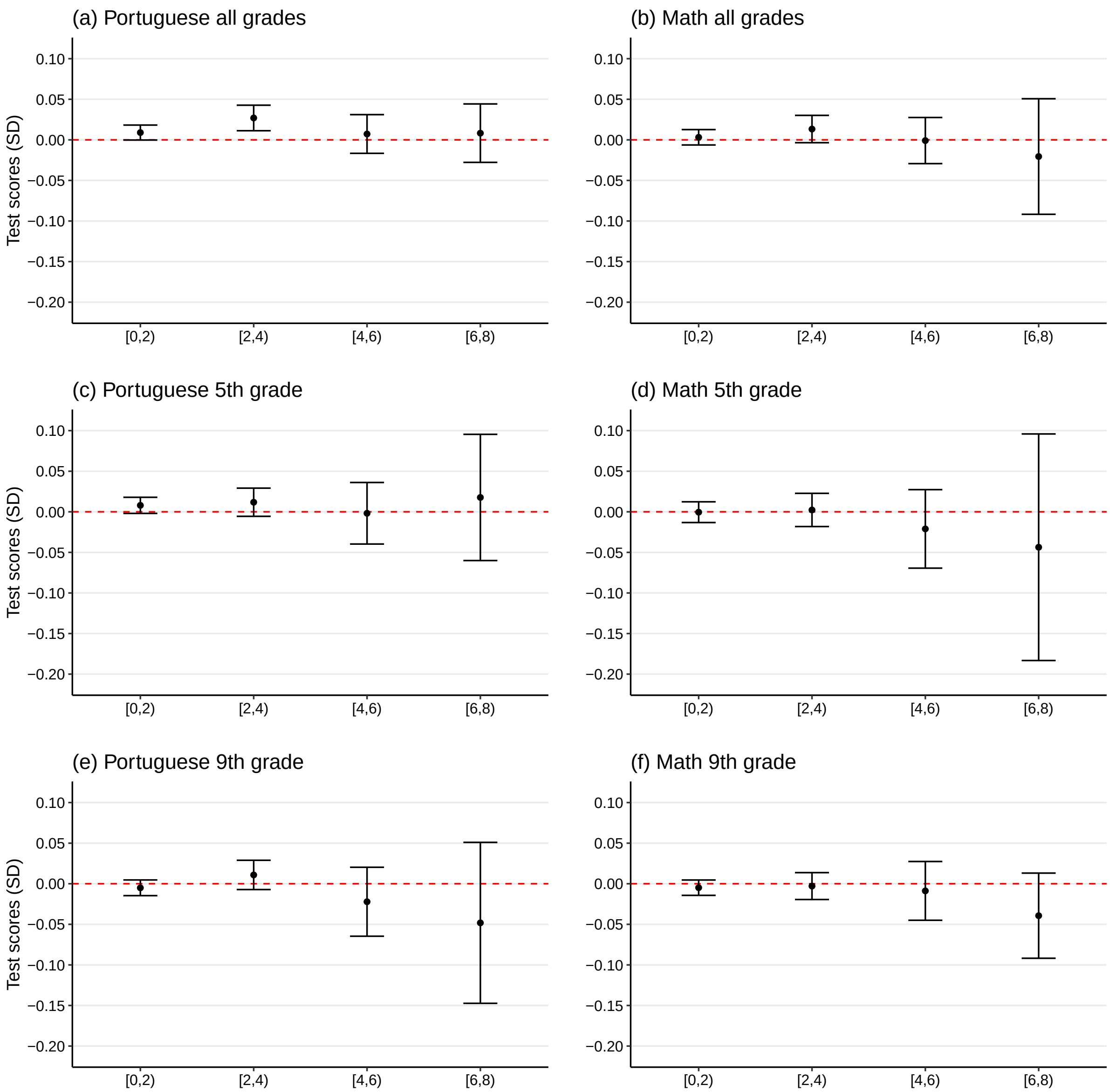
where penetration_{it} is the number of 3G/4G subscriptions as a share of population in DDD region i at year t. The variable share population treated_{it} is the inner product between the population in each municipality in i at t (IBGE) and the dummy capturing whether each municipality had 3G coverage at t. We include time FEs δ_t in the regression. The whiskers represent 95% confidence intervals, and we cluster standard errors by DDD region. The coefficients should be interpret as how a 1 percentage point change in population treated at year t affects the share of 3G subscriptions.

Figure 4: Evolution of 3G Coverage and Internet Usage by Kids 9-17 Years Old



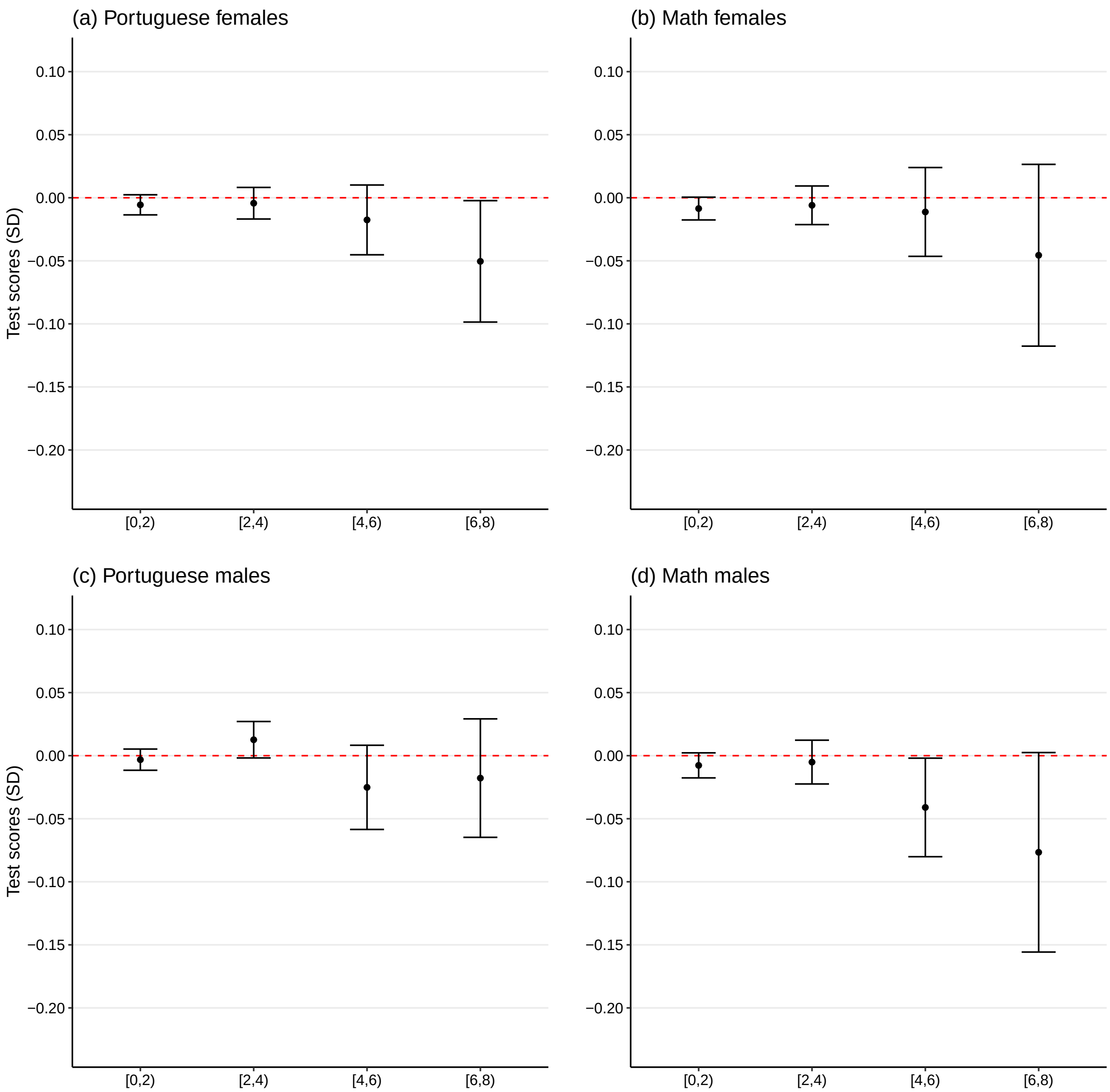
Note: This graph plots the percentage of kids 9-17 years old using the internet (vertical axis) and the evolution of percentage of municipalities covered by 3G (horizontal axis), by region for years 2015 and 2016. Internet use can be from any source (phone, computer, tablet, etc.).

Figure 5: Dynamic Effects of Mobile Internet on Test Scores (Robust DID Estimator)



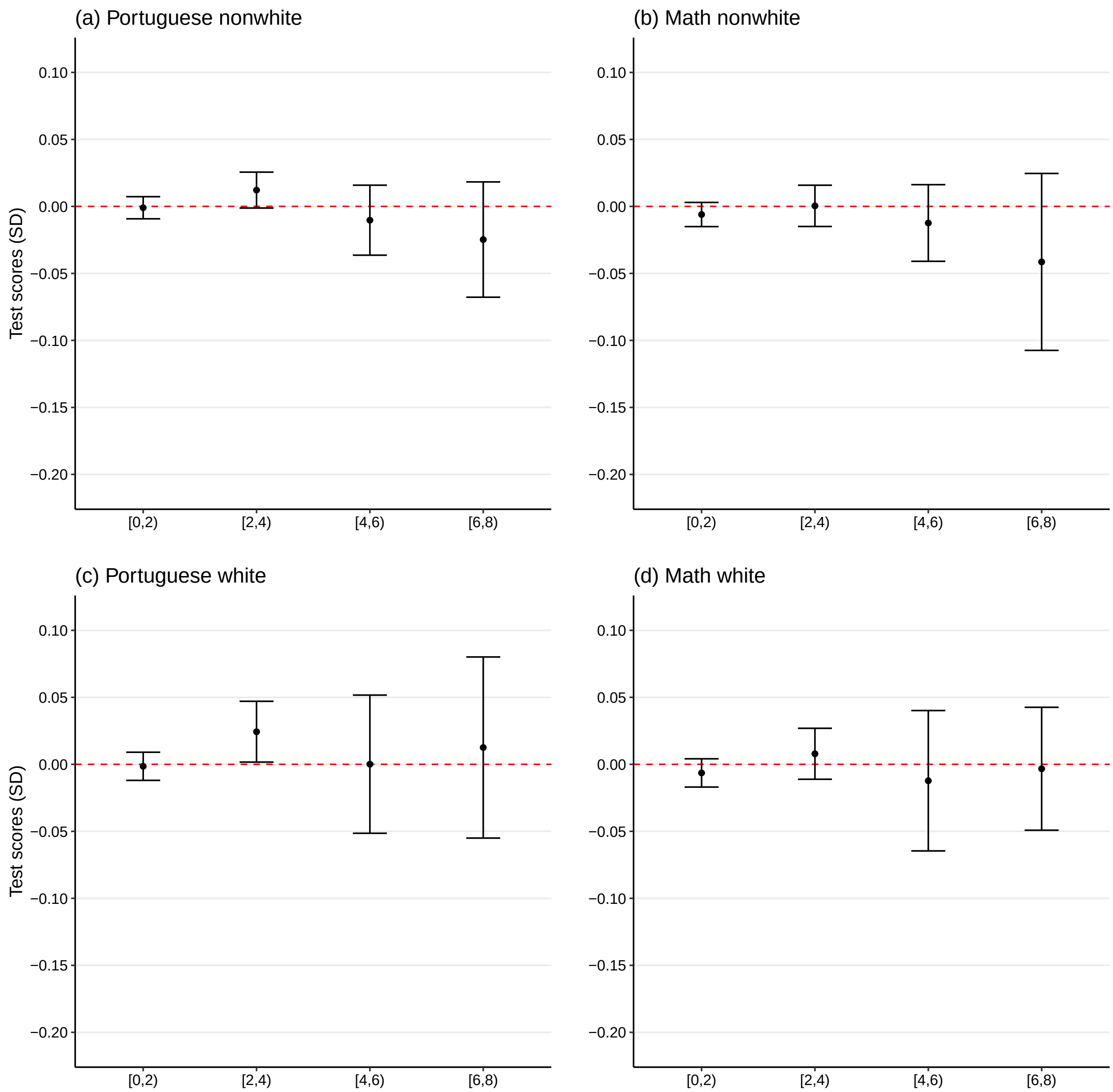
Note: This figure shows the estimates from the robust differences-in-differences estimator (de Chaisemartin and D'Haultfœuille, 2020) discussed in Section 5.1. The bars represent 95% confidence intervals.

Figure 6: Heterogeneous Treatment Effects: Students' Gender



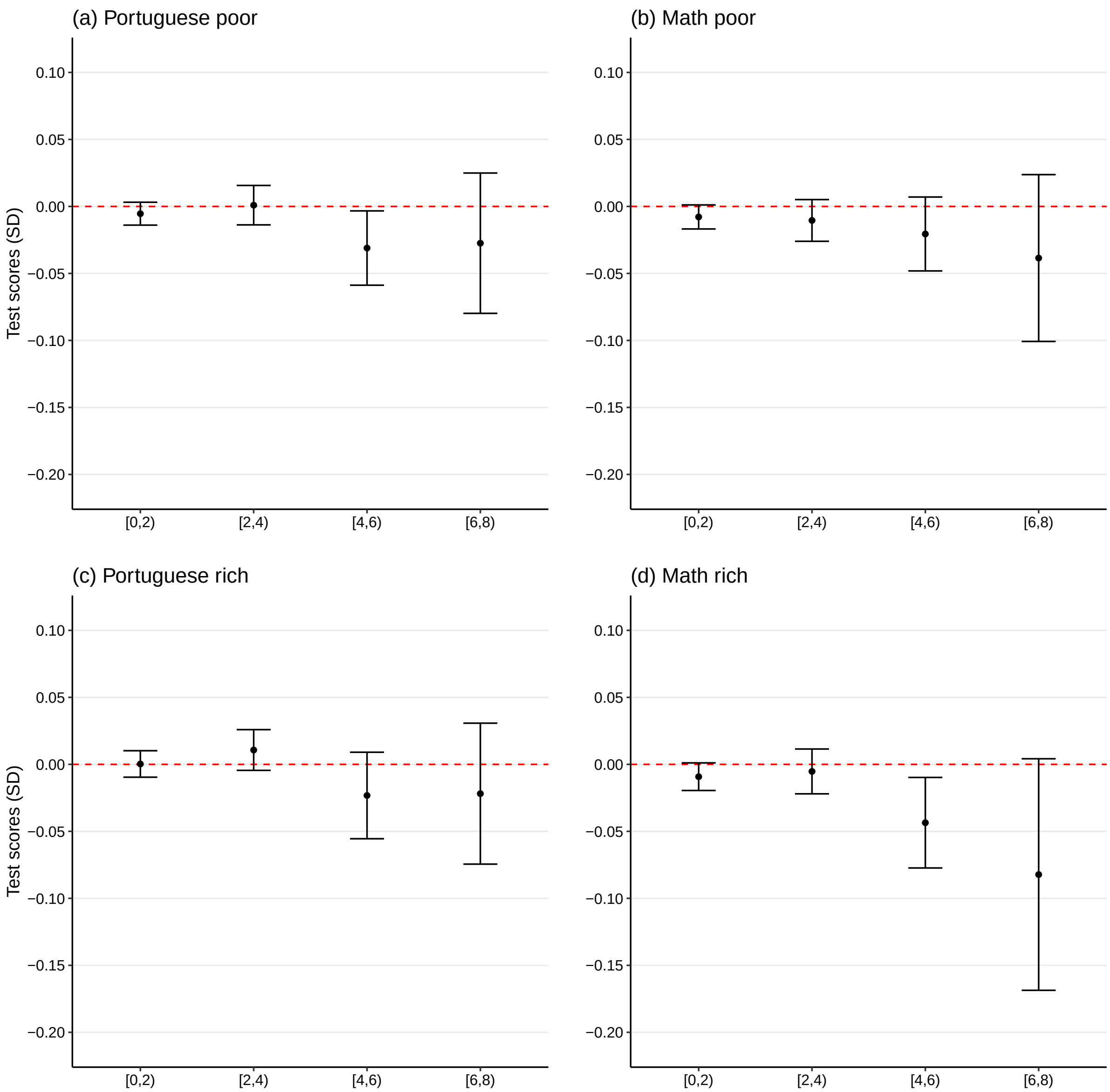
Note: This figure shows the estimates from the robust differences-in-differences estimator (de Chaisemartin and D'Haultfœuille, 2020) discussed in Section 5.1. The bars represent 95% confidence intervals. We pool the two grades together.

Figure 7: Heterogeneous Treatment Effects: Students' Race



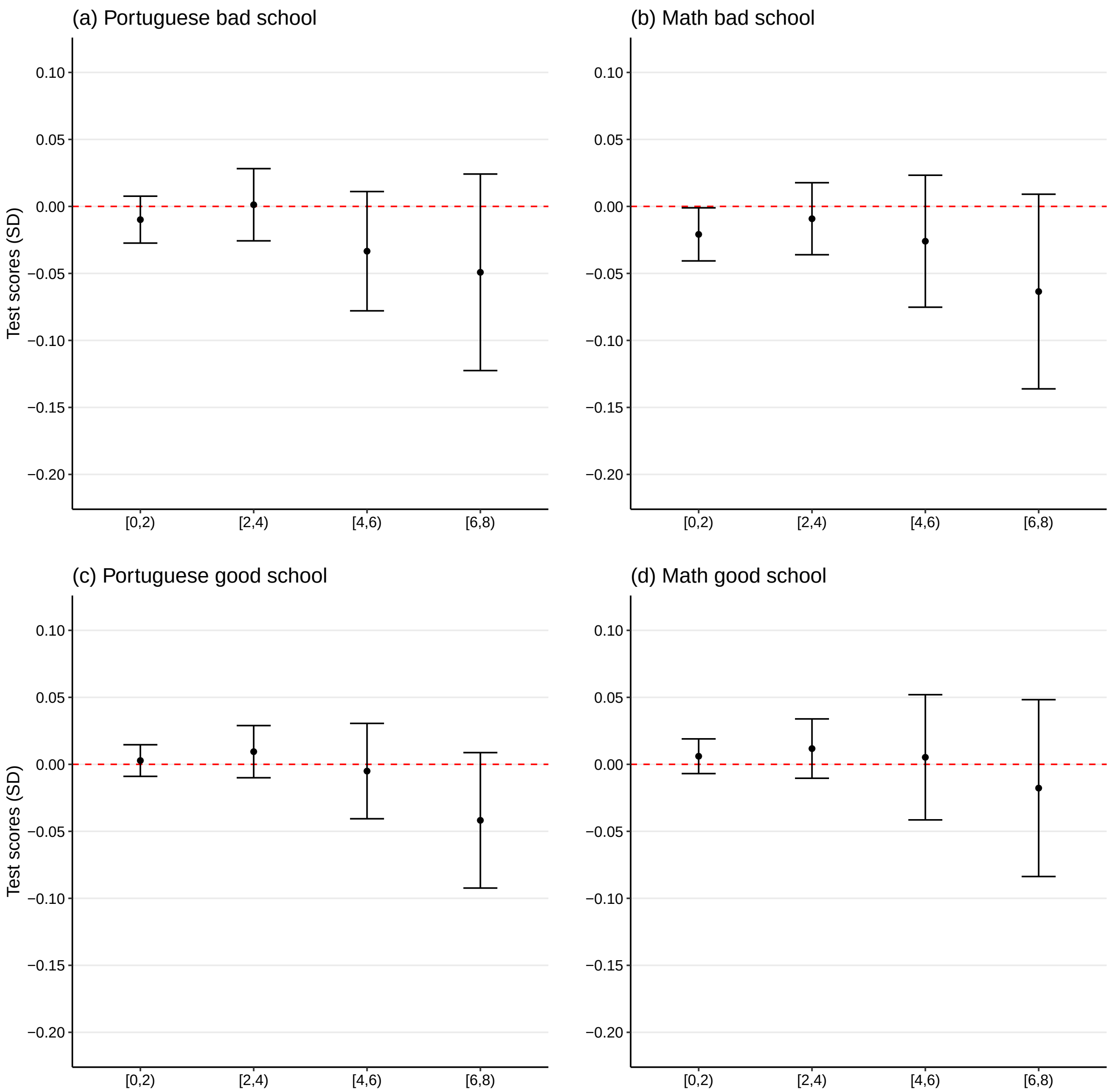
Note: This figure shows the estimates from the robust differences-in-differences estimator (de Chaisemartin and D'Haultfœuille, 2020) discussed in Section 5.1. The bars represent 95% confidence intervals. We pool the two grades together.

Figure 8: Heterogeneous Treatment Effects: Students' Wealth



Note: This figure shows the estimates from the robust differences-in-differences estimator (de Chaisemartin and D'Haultfœuille, 2020) discussed in Section 5.1. A student is deemed *poor* (*rich*) if his or her family stands below (above) the municipality's median income as reported in the *Prova Brasil* questionnaire. The bars represent 95% confidence intervals. We pool the two grades together.

Figure 9: Heterogeneous Treatment Effects: School's Baseline Test Scores



Note: This figure shows the estimates from the robust differences-in-differences estimator (de Chaisemartin and D'Haultfœuille, 2020) discussed in Section 5.1. A student is deemed *bad* (*good*) if its test score average stands below (above) the municipality's median test score as observed in the *Prova Brasil* data. The bars represent 95% confidence intervals. We pool the two grades together.

Online Appendix

A Tables and Figures

Table A.1: Effects of 3G on Students Test Scores - Unweighted Regression

	All grades		5th grade		9th grade	
	Portuguese	Math	Portuguese	Math	Portuguese	Math
	(1)	(2)	(3)	(5)	(6)	(8)
6-8 years before	0.028	0.018	0.046	0.046	0.014	-0.008
	(0.013)	(0.017)	(0.017)	(0.021)	(0.015)	(0.020)
	[0.033]	[0.288]	[0.008]	[0.025]	[0.356]	[0.689]
4-6 years before	-0.013	-0.016	-0.009	-0.014	-0.006	-0.005
	(0.008)	(0.009)	(0.010)	(0.012)	(0.013)	(0.012)
	[0.099]	[0.091]	[0.384]	[0.236]	[0.654]	[0.657]
2-4 years before	-0.001	0.003	-0.010	-0.011	-0.001	0.005
	(0.007)	(0.007)	(0.008)	(0.009)	(0.007)	(0.007)
	[0.924]	[0.677]	[0.236]	[0.189]	[0.923]	[0.478]
0-2 years after	0.004	-0.009	-0.002	-0.014	0.004	-0.004
	(0.007)	(0.006)	(0.007)	(0.009)	(0.006)	(0.007)
	[0.610]	[0.137]	[0.811]	[0.100]	[0.524]	[0.554]
2-4 years after	0.009	-0.013	-0.012	-0.031	0.026	0.004
	(0.012)	(0.013)	(0.013)	(0.015)	(0.016)	(0.012)
	[0.479]	[0.306]	[0.330]	[0.035]	[0.113]	[0.717]
4-6 years after	-0.040	-0.047	-0.051	-0.078	-0.023	-0.012
	(0.017)	(0.018)	(0.019)	(0.027)	(0.029)	(0.026)
	[0.019]	[0.008]	[0.008]	[0.003]	[0.434]	[0.654]
6-8 years after	-0.024	-0.058	-0.014	-0.069	-0.030	-0.035
	(0.018)	(0.028)	(0.031)	(0.053)	(0.039)	(0.023)
	[0.192]	[0.038]	[0.667]	[0.196]	[0.436]	[0.126]

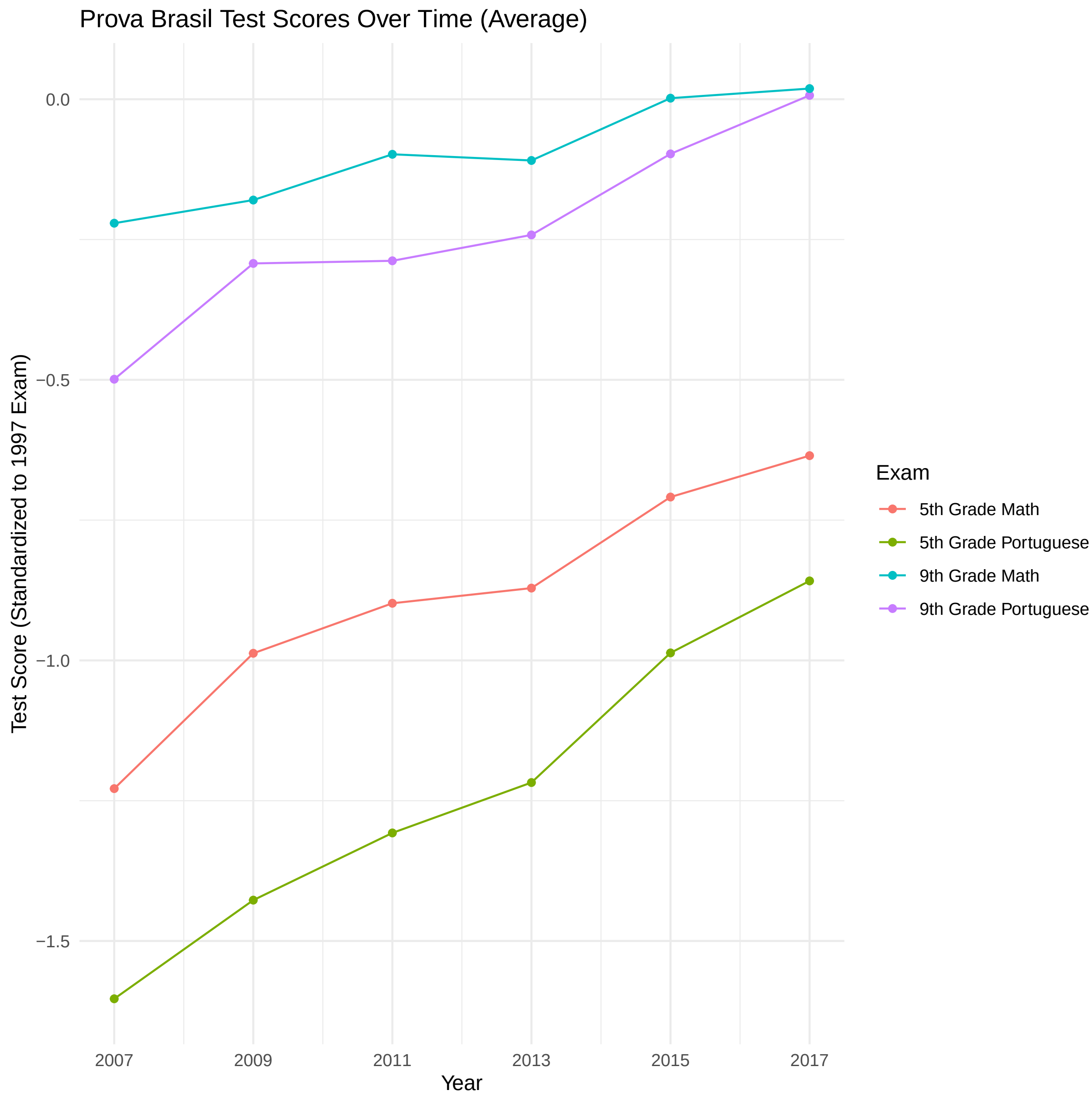
Note: This table shows the estimates from the unweighted robust differences-in-differences estimator (de Chaisemartin and D'Haultfœuille, 2020) discussed in Section 5.1. Standard errors clustered at the municipality level are presented under ( ). P-values are presented under [ ].

Table A.2: Two-way Fixed Effects - Effect of 3G on Student Test Scores

	5th Grade		9th Grade	
	Portuguese	Math	Portuguese	Math
6-8 years before	-0.004	-0.004	0.002	0.004
	(0.008)	(0.010)	(0.008)	(0.008)
4-6 years before	0.005	-0.001	0.005	0.003
	(0.007)	(0.009)	(0.006)	(0.006)
2-4 years before	0.003	0.003	0.006	0.004
	(0.005)	(0.006)	(0.004)	(0.004)
0-2 years after	0.000	-0.008	-0.008	-0.006
	(0.005)	(0.007)	(0.004)	(0.004)
2-4 years after	0.006	-0.001	-0.007	-0.007
	(0.010)	(0.011)	(0.007)	(0.007)
4-6 years after	0.017	0.012	-0.024	-0.021
	(0.014)	(0.017)	(0.010)	(0.010)
6-8 years after	0.024	0.008	-0.024	-0.018
	(0.018)	(0.021)	(0.014)	(0.014)
8-10 years after	0.041	0.018	-0.013	-0.005
	(0.024)	(0.028)	(0.019)	(0.019)
Pooled (before vs after)	-0.009	-0.013	-0.005	-0.005
	(0.005)	(0.006)	(0.004)	(0.004)
Municipality FE	x	x	x	x
State $\times$ Year FE	x	x	x	x

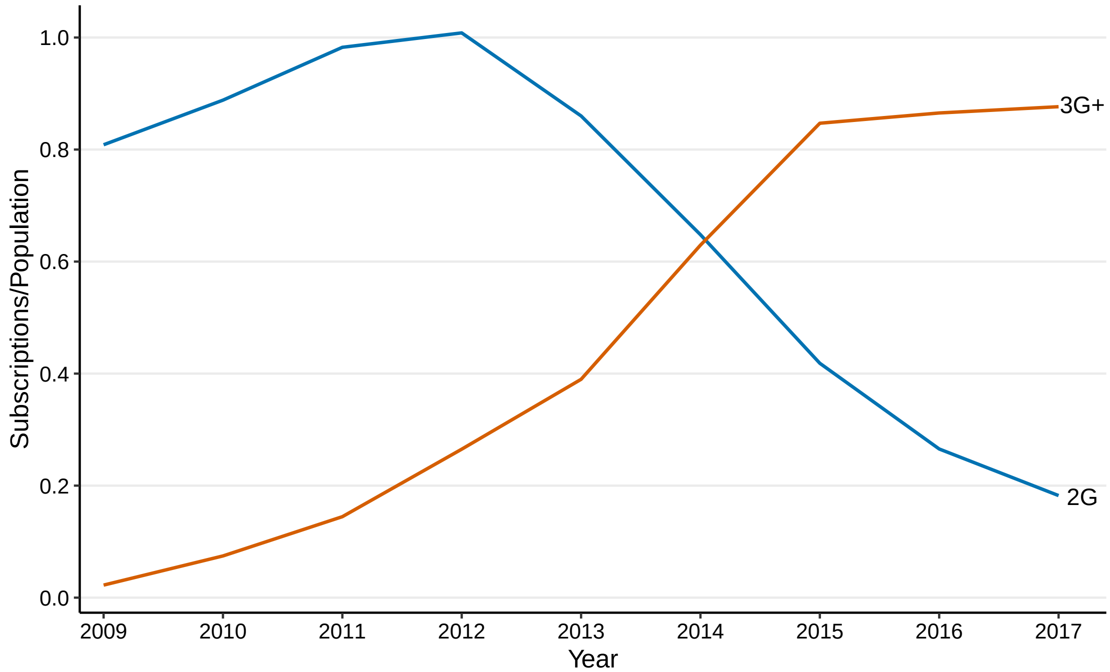
Notes: These estimates report results from Equation (1) studying the effect of 3G coverage on students' exam scores in Brazil as discussed in Section 5.2. Portuguese and math scores for 5th and 9th grade students come from the Prova Brasil, a national exam administered by the Ministry of Education every other year. Our sample covers the 2007-2017 exams. We exclude municipalities which already had 3G coverage before the start of our sample in 2008, municipalities which continued to not have 3G at the end of our sample in 2016, and municipalities which are missing for some year of our sample. These exclusions leave us with 4403 municipalities in our event studies. 3G coverage data from 2008-2016 is provided by ANATEL, the Brazilian national telecommunications agency. Standard errors clustered at the municipality level in parentheses.

Figure A.1: Prova Brasil Test Scores Over Time



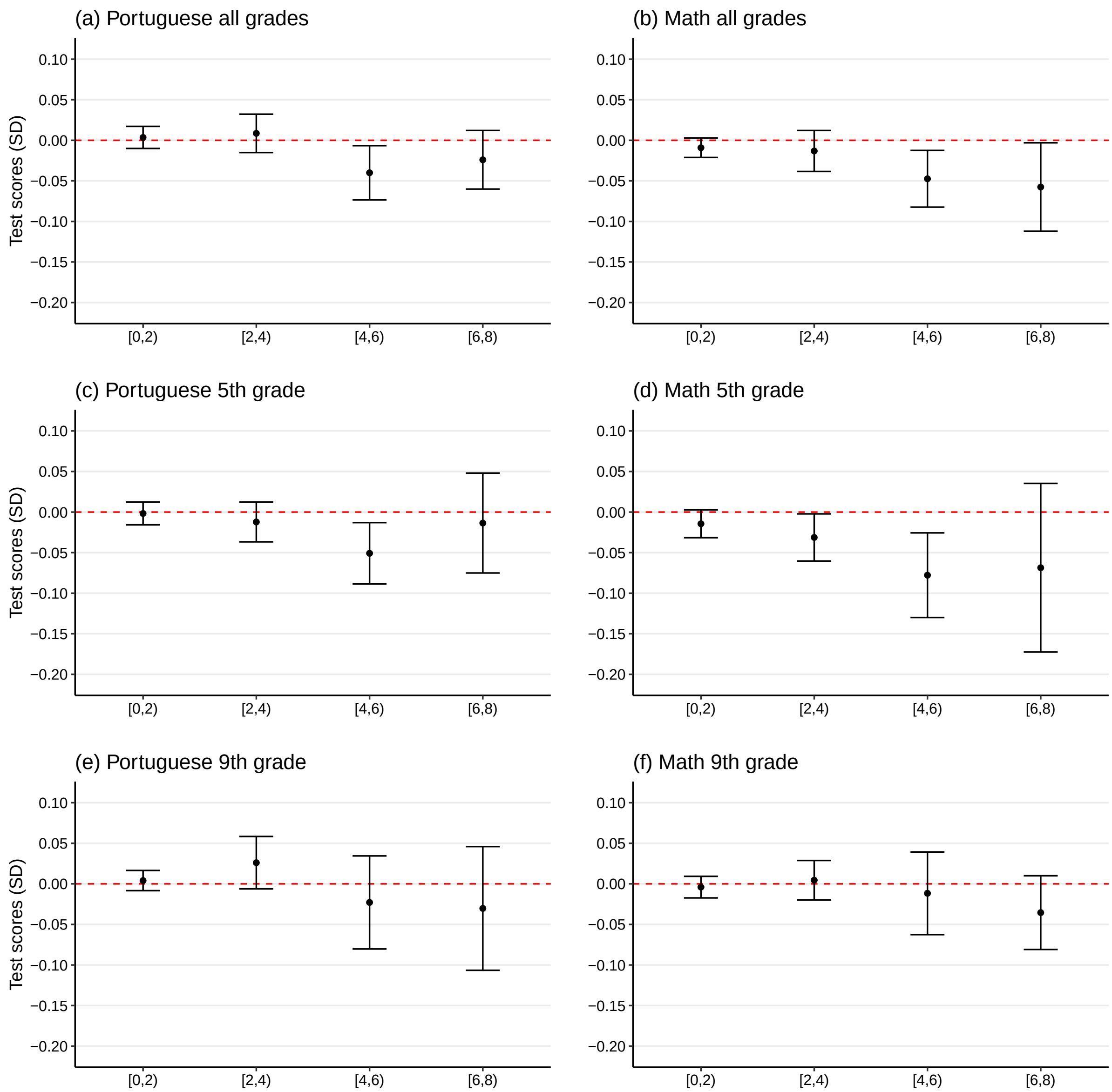
Note: This plot captures the time path of national average Prova Brasil test scores over time. Test scores are measured in standard deviations, normalised against the 1997 Prova Brasil. Students' Portuguese and math scores increase over time for both 5th grade and 9th grade. The 5th grade averages are constructed from approximately 1.2 million observations per year for each subject. There are approximately 1.0 million observations per year for 9th grade.

Figure A.2: Evolution of Mobile Internet Usage



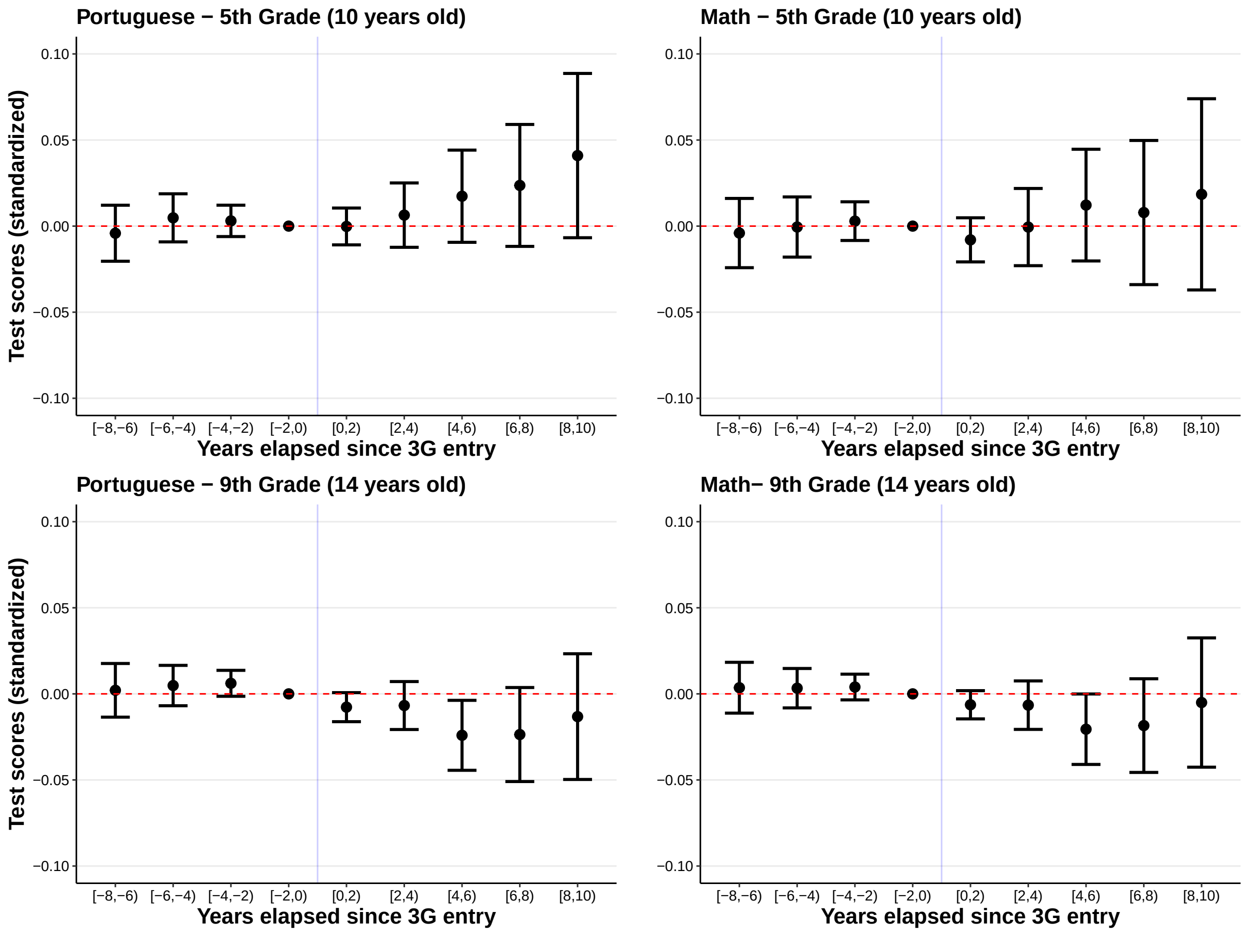
Note: This figure shows the evolution of 2G (blue) and 3G/4G (orange) internet penetration (subscriptions/population) in Brazil between 2009 and 2017. Subscriptions are measured as the number of devices with access to 2G, 3G and 4G internet plans (ANATEL). The penetration of 2G went from 100% at its peak in 2012 to 18% in 2017. 3G/4G in contrast, went from 2% in 2009 to 88% in 2017.

Figure A.3: Dynamic Effects of Mobile Internet on Test Scores (Robust DID Estimator) - Unweighted regressions



Note: This figure shows the estimates from the unweighted robust differences-in-differences estimator (de Chaisemartin and D'Haultfœuille, 2020, 2021) discussed in Section 5.1. The bars represent 95% confidence intervals.

Figure A.4: Two-Way Fixed Effects Event Study: Effect of 3G Coverage on Test Scores



Note: These graphs plot our two-way fixed effects event study from Equation (1) and discussed in Section 5.2, where the "event" is the start of 3G coverage, and the outcome is children's scores on the Prova Brasil standardized relative to the 1997 exam. The Prova Brasil is administered every other year to 5th and 9th grade students nationally. Our sample includes test scores from the 2007-2017 exams. We exclude municipalities which already had 3G coverage before the start of our sample in 2008, municipalities which continued to not have 3G at the end of our sample in 2016, and municipalities which are missing for some year of our sample. These exclusions leave us with 4403 municipalities in our event studies. This specification includes two-way fixed effects (municipality and state-by-year). The confidence intervals are at the 95% level, with standard errors clustered at the municipality level.