Mobile Internet Has No Impact on Educational Outcomes: Evidence from Brazil*

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Abstract

What is the impact of mobile broadband internet on children's educational outcomes? We compare standardized test scores before and after the staggered entry of 3G into Brazilian municipalities using a heterogeneity-robust event study design. We find no effect on test scores for 5th or 9th grade students, and can reject effects of 0.01 standard deviations in both math and Portuguese two years after 3G adoption. Following exam results up to eight years after the arrival of high-speed mobile internet, we continue to find no improvement to test scores, in spite of high adoption rates of 3G mobile broadband subscriptions.

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1 Introduction

The number of internet users 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 improve educational outcomes in developing countries. International organizations and national governments alike adopted the cause of universal internet access, including in developing countries such as Brazil, Indonesia, and Nigeria.[1] Although it does appear that expanding internet access in developing countries may result in economic development in the form of higher employment and wages (Hjort and Poulsen, 2019), there is little evidence thus far to support the other justification that internet access can increase educational achievement.[2]

In this paper, we leverage the staggered rollout of mobile internet across Brazilian municipalities to estimate the impact of mobile internet on educational outcomes. We focus on the expansion of the 3G network, which was the first generation of telecommunications technology that allowed users to easily access most features of the internet.[3] Cellphones are the most common and quickly expanding means to access the internet in Brazil and in other developing countries (Bahia and Suardi, 2019), making it important to study the impacts of *mobile* internet in particular.

We explore the effect of 3G entry on Portuguese and math test scores between 2007 and 2015 using data from the *Prova Brasil*, a standardized exam taken by nearly all 5th and 9th grade students in Brazilian public schools every other year. Because municipalities which received 3G in earlier versus later years may have different characteristics which affect test scores, we use an event-study research design to estimate the effects of 3G treatment. The treatment effects of 3G are likely to have evolved over time as the ecosystem of mobile applications became more sophisticated, and so we estimate treatment effects which are robust to heterogeneity using the methodology proposed by de Chaisemartin and D'Haultfœuille (2020, 2021). These estimates are robust to negative weighting problems

[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 both emerging and established economies (e.g. China and India), are pursuing industrial policies to promote their domestic digital economy.

[2] An example claim about the impact of internet access on economic development and educational outcomes from the Nigerian government's 2020-2025 National Broadband Plan: "Rapid rollout of broadband services will address various socioeconomic challenges faced by the country, including the need to grow its economy, create jobs, rapidly expand the tax base, and *improve digital literacy and educational standards*."

[3] 2G allowed users to send texts, 3G facilitated social media use and web browsing, and 4G allowed for video streaming (Woyke, 2018).

inherent to two-way fixed effects event study designs that have been highlighted in recent literature (e.g., Callaway and Sant'Anna, 2020; Abraham and Sun, 2020; Borusyak et al., 2021). We also complement this analysis with standard two-way fixed effects regressions.

Our results show that the availability of 3G internet does not impact test scores in Portuguese and math in the short- or long-run. We report findings in three steps. First, we show that our measures of 3G coverage did translate into increased use of mobile internet. Combining mobile internet subscriptions with the data on 3G entry into municipalities, we find that by the end of our study period in 2016, a 1 percentage point (pp) increase in the population covered by 3G is associated with an increase of 0.77pp in mobile internet subscriptions per capita.

Second, 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 eight years after entry. We are powered to detect effect sizes as small as 0.01 standard deviations (SD) in the two years following the arrival of 3G in both Portuguese and math.[4] In later years, the estimates are less precise, but we are still powered to detect positive effects as small as 0.039SD four to six years after 3G entry.

Third, our null results are not driven by low mobile internet adoption rates at the beginning of our sample period or by low use of mobile internet among children and adolescents. Specifically, our conclusions hold when restricting attention to a shorter panel containing years when adoption of mobile internet was more universal (2013 and 2015). In addition, surveys of children and adolescents in Brazil report internet usage rates which range from 54% in the poorest region to 90% in the richest region by 2015.

In sum, despite widespread enthusiasm about the potential for internet access to improve educational outcomes in developing countries, the entry of 3G mobile internet had no effect on test scores in Brazil. If decisions to support national broadband investments have internalized an expectation of positive educational impacts, this paper offers a sobering reminder that the provision of technology alone is unlikely to have effects on education, even modest ones which incorporate equilibrium effects over a long time window. This overoptimism seems at least partially due to a misprediction about what individuals would use the internet to do; largely they used it for leisure, which did not increase learning that could be reflected in standardized tests.[5] Perhaps mobile internet could be lever-

[4] Our data give us enough precision to detect these small effects with 80% power at the 95% significance level. Minimum detectable effects are calculated as 2.8*(standard error) here and in the rest of the paper as the estimator is asymptotically normal. The 95% confidence intervals on these estimates are [-0.006, 0.010] (Portuguese) and [-0.011, 0.005] (math).

[5] Worldwide, mobile internet use largely consists of social media engagement. In Brazil, internet users aged 16-64 report using their mobile devices to access internet services for 4 hours 41 minutes on average each day, of which 3 hours 31 minutes are spent on social media (Kemp, 2020).

aged to increase student learning, but this might require a more active approach which does not seem to arise without policymakers' involvement when internet services are introduced (e.g. coordinated efforts by educators and policymakers to build and adopt complementary internet-based educational software).

This paper contributes to three strands of literature. First, we build on previous studies which explored the impact of internet on educational outcomes. To date, the literature has focused mostly on fixed (wired) broadband internet and high-income countries (Faber et al., 2015; Fairlie and Robinson, 2013). In contrast, we provide 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 Malamud et al. (2019) in three important respects: first, our estimates account for any general equilibrium effects of internet provision, which are not present in experiments which vary access at the student level; second, we estimate long-run effects, which may be important for the causal channels considered by policymakers who contemplate building internet infrastructure; third, we focus on mobile internet rather than computer-based internet.[6]

Second, we add to previous work about the effects of other (non-internet) information and communications technology (ICT) on education. In different settings, evaluations of programs providing personal computers to students showed zero (Beuermann et al., 2015) or negative effects (Malamud and Pop-Eleches, 2011). However, in these studies, there is no significant difference in internet access between treatment and control groups. Our paper shows that even when high-speed internet is available for a widely used technology (cellphones), the educational benefits are small or nonexistent.

Third, we contribute to 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 in a sample of twelve African countries. Our results suggest that these labor market gains may not translate into gains in educational achievement, or that mobile internet does not lead to comparable labor market gains.

[6] Most individuals in developing countries have better knowledge of how to proficiently use a mobile phone rather than a computer, and families are more likely to have multiple cellular devices.

2 Setting

2.1 The education system in Brazil

We focus on students in grade 5 (age 10) and grade 9 (age 14), the two years in which students take the *Prova Brasil*, a biennial national exam. The exam is mandatory in public schools, and grade 9 is the the last year of mandatory schooling. Students may attend either public or private schools, but the majority (approximately 80%) attend public schools. Our sample includes all students in municipalities treated with 3G between October 2008 and June 2016 who attended public schools large enough to have publicly-reported *Prova Brasil* scores.[7] Thus the test scores that we consider in our study are representative of a large majority of school students in Brazil during the time period of mobile internet expansion.

If internet access is beneficial to students with low baseline levels of learning (e.g. because the materials provided online are only beneficial to those without better in-person resources available), then Brazil is a promising setting to investigate the potential of internet to improve student test scores. At the start of our sample period in 2009, Brazilian students scored far below the OECD average on the international PISA exam which is often used to compare education systems across countries. The average Brazilian student scored 412 in reading (OECD average: 493) , 386 in math (OECD average: 496), and 405 in science (OECD average: 501). Ten years later in 2018, nearly half (43%) of Brazilian 15-year-olds scored below the minimum level of proficiency (Level 2) in all three subjects of the international standardized PISA exams, as compared to the OECD average of 13% (Schleicher, 2019). Only half of students scored at minimum proficiency in reading, and even fewer (32%) reached minimum proficiency in math.

2.2 3G internet

"3G" refers to the third generation of wireless mobile telecommunications technology and the first to be considered broadband due to fast data transfer speeds. In comparison to 2G, 3G allows users to access websites, use social media, and even to (slowly) watch online videos from their phones. Using 2G technology, phones were limited to text messaging and very light web browsing. The next generation (4G), allowed users to stream content and participate in video calls, which was not feasible under 3G. Because this transition is usually considered the first conversion to mobile broadband, our study focuses on the

[7] 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.

entry of 3G mobile internet.

2.2.1 Institutional background

Large private providers were responsible for the rapid expansion of Brazil's 3G network. The path of 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 to private companies. In this and subsequent auctions, ANATEL imposed requirements to reach sparsely populated regions of the country where the provision of 3G internet would not be profitable.[8]

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 connections would be implemented in each municipality. Implementation was successful: by the end of 2019, the target year for universal 3G access in Brazil, 99.98% of the population had access to 3G.

2.3 Data

Education. The main educational outcome is exam scores from the *Prova Brasil*, a nationwide exam administered every other year to all 5th and 9th grade students in Brazilian public schools.[9] Figure A.1 summarizes the trends in Portuguese and math scores from 2007 to 2017. Our data include test scores for approximately 2.2 million students per year. We use the exam score standardization provided by the *Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira* (Inep), the government agency which benchmarks the scores against a 1997 exam to make the test scores comparable across years.

3G coverage. 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. We consider a municipality to be treated with 3G in year t if 3G started operating in that municipality by October

[8] More specifically, ANATEL imposed targets for the 3G network based on population, but these targets were nearly always surpassed and do not appear to be binding in our study sample.

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

(inclusive) of year t. Because *Prova Brasil* takes place in November, if a municipality received 3G in November or December of year t, we define the first year of treatment as $t + 1$.

Mobile internet subscriptions. Data about the number of mobile internet subscriptions by municipality-year between 2008 and 2016 is from ANATEL. Figure A.2 plots the evolution of 2G, 3G, and 4G penetration in Brazil over the course of our study period. 3G and 4G mobile internet subscriptions increase sharply over time, from only 2% of all cellphone subscriptions in 2009 to 88% in 2017.

Children's internet usage. Data about the patterns of children's internet usage is from the TIC Kids Online survey, available during 2015-2018 for ages 9-17 from the *Centro Regional de Estudos para o Desenvolvimento da Sociedade da Informação* (CETIC). The survey includes information such as online activities, social media use, and supervision by parents. Because of small sample sizes and privacy regulations, the data are only available at the regional level.

Other data sources. We use data on municipality population and GDP from the Brazilian Institute of Geography and Statistics (IBGE), and municipality socioeconomic characteristics from the 2000 and 2010 Censuses. These are used to construct summary statistics of the municipalities which receive 3G in each year (reported in Table A.1).

3 Translating 3G coverage into internet usage

In order for 3G entry to have had an effect on educational outcomes, it is necessary that 3G coverage translated into higher take up of mobile internet subscriptions.

3G coverage and smartphone use expanded rapidly in Brazil during the study period. From 2008 to 2016, the share of municipalities with 3G coverage jumped from 5% (305) to 87% (4831), (Figure 1). This geographic increase in 3G coverage was accompanied by an increase in the use of smartphones, which are devices designed to access mobile internet. The market share of smartphones soared: in 2009, only 860,000 smartphones were sold as compared to 25.6 million "dumb" phones, but by 2016, yearly smartphone sales had reached 43.5 million, or 89% of the cellphone market (Figure A.3).

Penetration of mobile broadband internet, measured by the number of 3G or 4G subscriptions per capita, also increased rapidly during the study period. Figure 2 shows the evolution of state-level mobile broadband penetration between 2010 and 2016.[10] In 2010, less than 10% of the population in all but two states (one of them is Brasilia, the country's

[10] Municipality-level data on 3G subscriptions is only available from 2019.

capital city) subscribed to 3G/4G services. Only two years later, all municipalities had between 10% and 50% 3G/4G penetration. By 2016, all municipalities had 3G/4G penetration levels of at least 50%, with most over 70%. Overall, from 2009 to 2017 the number of subscriptions jumped from 2 to 88 per 100 inhabitants, reaching over 50 mobile broadband internet subscriptions per capita by 2014.

These changes in mobile internet penetration are highly correlated with our measures of 3G coverage. We use data on 3G/4G subscriptions to construct the share of the population which subscribes to 3G/4G services at the DDD area level.[11] In Figure 3, we correlate this variable with the share of the DDD population in municipalities with 3G coverage. Although we cannot interpret the evidence causally, Figure 3 suggests that at the beginning of our sample period, 3G coverage is associated with a modest increase in subscriptions, and that this relationship is strongly increasing over time. In 2009, a 1 percentage point (pp) increase in population treated with 3G coverage is associated with a 0.03pp increase in mobile internet subscriptions. However, between 2014 and 2016, subscriptions increase by 0.61pp-0.77pp when an additional 1pp of the population is treated with 3G coverage.

It is worth noting that cellphones are usually the primary (and often only) means to access the internet in Brazil and other low- and middle-income countries. In 2014, Brazil had 134 mobile phone subscriptions per 100 inhabitants, and only 10.5 fixed broadband internet subscriptions per 100 inhabitants (World Bank). Therefore the arrival of 3G mobile internet coverage and subsequent increase in mobile internet subscriptions likely represents an increase in any internet access at all.

4 Effects of mobile internet on test scores

4.1 Empirical Strategy: Robust Difference-in-Differences

We use variation in the timing of 3G entry into municipalities across Brazil to quantify its effects on educational outcomes. We estimate the dynamic effects of 3G coverage on students' outcomes using an event study strategy that controls nonparametrically for state-time trends. Unlike in standard two-way fixed effects (TWFE) regressions, we allow for heterogeneous treatment effects across cohorts using the difference-in-differences estimators proposed in de Chaisemartin and D'Haultfœuille (2020, 2021). The key identifying

[11]DDD regions are comparable to U.S. area codes. There are 67 DDD areas in Brazil, each of which is a subset of a state. We were unable to obtain 3G/4G subscription data at a more disaggregated geographic level for our time period.

assumption for our difference-in-differences specification is that student outcomes within states would have evolved on parallel trends in the absence of 3G adoption. The parallel trends assumption in our context allows us to interpret divergence from these test score trajectories timed to the entry of 3G coverage as treatment effects of mobile internet. We provide support for the parallel trends assumption and demonstrate the importance of allowing for treatment effect heterogeneity in our context below.

4.1.1 Estimation of Treatment Effects

The dynamic treatment effects that we estimate are a weighted average of difference-in-difference estimators derived from municipalities which were treated in different years of our study period (de Chaisemartin and D'Haultfœuille, 2020, 2021).

Set Up. Let $3G_m$ denote the time period that municipality m received 3G. Let $Y_{m,t}$ be the average outcome of students in municipality m at time t, and $N_{m,t}$ be the number of students we observe in municipality m at time t. Then define $N_t^{t-l} = \sum_{m:3G_m=t-l} N_{m,t}$ to be the number of students at time t living in municipalities that received 3G coverage for the first time in period $t-l$. This is the sum of students across municipalities treated at $t-l$. Similarly, define $N_t^{NT} = \sum_{m:3G_m>t} N_{m,t}$ to be the number of students in municipalities which still do not have 3G coverage at time period t.

Effect of $l+1$ periods of treatment for cohort treated at $t-l$. An important building block of the dynamic treatment effects is an unbiased estimator of the cumulative effects of 3G coverage over $l+1$ time periods for students living in municipalities which received 3G coverage at time period $t-l$, denoted $DID_{+,t,l}$. This term compares the time path of outcomes from time period $t-l-1$ to time period t for municipalities which received 3G at $t-l$ to municipalities which have not yet received 3G at t. The time path of outcomes for municipalities which had not received 3G yet at time t serves as a counterfactual for municipalities which received 3G at time $t-l$. At time t, students in municipalities which received 3G at $t-l$ are reaching $l+1$ periods of mobile internet coverage, so $DID_{+,t,l}$ is an unbiased estimator of the effect of having 3G for $l+1$ periods at time t.

$$DID_{+,t,l} = \sum_{m:3G_m=t-l} \frac{N_{m,t}}{N_t^{t-l}}(Y_{m,t} - Y_{m,t-l-1}) - \sum_{m:3G_m>t} \frac{N_{m,t}}{N_t^{NT}}(Y_{m,t} - Y_{m,t-l-1}) \quad (1)$$

Average effect of being treated for $l+1$ periods. $DID_{+,l}$ is an unbiased estimator of the average effect of having 3G coverage for $l+1$ time periods across all treatment cohorts, and is built as a weighted sum of $DID_{+,t,l}$.

$$DID_{+,l} = \frac{\sum_{t=l+2}^{NT} N_t^{t-l} \beta_t DID_{+,t,l}}{\sum_{t=l+2}^{NT} N_t^{t-l} \beta_t} \tag{2}$$

We plot our estimates of $DID_{+,l}$ for $l \in \{$-6 to -4, -4 to -2, 0-2, 2-4, 4-6, 6-8$\}$ in Figure 4 and report the same coefficients in Table A.2.

4.1.2 Tests of treatment effect heterogeneity

The more common event study strategy in a setting such as ours would be to use TWFE regressions. However, a series of recent papers demonstrates that TWFE regression estimators have undesirable properties when extended to settings with differential treatment timing (de Chaisemartin and D'Haultfœuille, 2020; Callaway and Sant'Anna, 2020; Abraham and Sun, 2020; Goodman-Bacon, 2020; Borusyak et al., 2021). In particular, if treatment effects are heterogeneous, then the estimated treatment effect from a TWFE linear regression can be a non-convex combination of conditional average treatment effects, with some treatment effects receiving negative weights. This problem applies both to estimators of overall treatment effects, which pool time periods before and after treatment, as well as to estimators which consider each event-time period individually.

In light of these issues, if the treatment effects of 3G mobile internet on students' outcomes were relatively homogeneous across cohorts, then the benefit of using a more widely understood estimation strategy might be worthwhile. However, 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, which would result in biased estimates using TWFE regressions. To support this conceptual argument, we quantify how problematic TWFE regressions would be in our setting, and demonstrate that very little treatment effect heterogeneity would be required for the TWFE regression coefficients to be incorrectly signed (e.g., for us to conclude that treatment effects are positive when in fact they are negative).

Using TWFE regressions, we could sign the treatment effects incorrectly under very mild treatment effect heterogeneity. Using calculations of the TWFE regression weights and the ratio of the TWFE coefficients to the standard deviation of these weights, we can show that the TWFE estimate may be incorrectly signed if the standard deviation of treatment effects is as small as 0.00060 (Portuguese) and 0.00206 (Math). Even if the cohort treatment effects were all positive or all negative, it would be possible for the TWFE estimate to be zero (or of the opposite sign) if the treatment effects had a standard deviation of 0.00124 (Portuguese) or 0.00424 (Math). We even find direct evidence that negative weights cause problems in the TWFE regressions in our setting: when we regress 5th grade Portuguese scores on 3G entry, we find that the overall estimated treatment effect is not a convex combination of the dynamic treatment effects (see Table A.3 Column 1). The full diagnostics of robustness to treatment effect heterogeneity are reported in Table A.4, and suggest that it is necessary to use a method which is robust to treatment effect heterogeneity in our setting.[12]

4.1.3 Evaluating the Parallel Trends Assumption

As is the case in other difference-in-differences estimation strategies, the key identifying assumption is that student outcomes would have evolved in parallel across municipalities within the same state in the absence of 3G entry. We make both a conceptual and empirical argument for the plausibility of this assumption. Conceptually, we exploit variation in 3G entry across municipalities which received 3G between June 2008 and October 2016, the time period covered by the data we were able to acquire. One advantage of focusing on this subset of municipalities, which are the 5th to 87th percentile of municipalities in terms of 3G arrival, is that we exclude the municipalities which are most likely to be on different trends in test scores. We exclude both the most developed, most populous municipalities such as Rio de Janeiro and São Paolo which had already received 3G by 2008, as well as the poorest and most rural muncipalities which had not yet received 3G by the end of 2016. Therefore our sample includes municipalities which are in the middle of the spectrum in terms of development, and are less likely to be outliers in terms of test score trends.

We also test the parallel trends assumption empirically. We estimate placebo effects which are comparable to our treatment effect estimators, except computed over a time period in which municipalities do not actually change their treatment status. These placebo estimators (proposed in de Chaisemartin and D'Haultfœuille (2021) as "long-difference placebos") test if common trends in outcomes hold over several periods across different groups. We show the details of the estimator in Section B.

The placebo test provides evidence that the parallel trend hypothesis holds in our setting. We plot the placebo estimates in Figure 4 and report the estimates with bootstrapped standard errors clustered at the municipality level in Table A.2. If the parallel trends assumptions hold, then the placebo estimators would not significantly differ from zero. We estimate these "long-difference" placebo estimators over two time periods which span 6

[12] For the sake of comparison, we do compute estimates from the two-way fixed effects regressions, and report them in Figure A.4 and Table A.3.

years before a municipality receives 3G. All the placebo estimates are close to zero and statistically insignificant. Most of the placebo estimates in each grade and subject subgroup are within 0.01SD of zero. These precisely estimated placebos suggest that the assumption of parallel trends in average outcomes across municipalities within the same state may be plausible in our context.

4.2 Results: Effect of 3G Mobile Internet on Students' Test Scores

We estimate precise zero effects of 3G mobile internet on students' test scores. Table A.2 and Figure 4 report the dynamic effects of 3G mobile internet on test scores using the robust difference-in-differences estimator. Within the first two years after 3G entry, we rule out effects as small as 0.011SD in both Portuguese and math. We can also reject a delayed effect of 3G on test scores. Even 8 years later, the effects remain close to zero and insignificant. For these later years, our estimates are less precise, but we are still powered to rule out effects as small as 0.039SD 4-6 years after 3G entry, with 95% CIs excluding positive effects of 0.015SD in either Portuguese or math. This suggests that there is no lagged effect of mobile internet through channels such as delayed take up of smartphones or changes to the broader economy.

We also estimate precise zero effects when disaggregating by school grade. In the two years following treatment, we can reject effects as small as 0.017SD in Portuguese and Math for 5th grade and 0.014SD in both subjects for 9th grade. The results are similar when looking at a longer time horizon. 4-6 years after 3G entry, we still find no effects, and are powered to reject effects as small as 0.07SD across all subgroups. Our study sample has fewer observations 8 years after 3G entry, but we still see no point estimate larger than 0.047 in magnitude.

These magnitudes are small in comparison to the effect sizes that other studies have found in our setting. Using the same standardized test, Akhtari et al. (2020) find that bureaucrat turnover reduces test scores by 0.05-0.08SD. Varjão (2019) find a similar effect size (0.09SD) from the introduction of local radio, which gives local politicians the incentive to invest more in education. For several years after 3G entry, we are able to rule out considerably smaller effects of mobile internet on test scores.

Two-Way Fixed Effects Regressions. We complement these heterogeneity-robust event study estimates with standard TWFE regressions and find similar results for the dynamic effects of 3G mobile internet on students' test scores. The estimates (presented in Figure A.4 and Table A.3) are close to zero throughout the 8 to 10 years after network providers begin offering 3G in the municipality.[13] The largest estimated effect is 0.04SD at the 8-10 year event time for 5th grade Portuguese, and this estimate is imprecisely estimated and statistically insignificant. For Portuguese, the event study shows a slight (insignificant) positive trend for 5th grade, and a slight negative trend for 9th grade.

However, given the negative weighting issues that arise from TWFE regressions we discuss in Section 4.1.2, these estimates are hard to interpret. As an example of the inadequacy of TWFE in our setting, we find that 3G has a positive (albeit insignificant) impact on 5th grade Portuguese test scores at any event-time period after treatment (column 1, table A.3). However, when we make the common assumption that treatment effects do not change over time (i.e., TWFE regression with a "post" dummy), we find a *negative* and significant impact of 3G on Portuguese test scores. This showcases that TWFE estimates are inadequate when treatment effects are heterogeneous, even in a setting with small effects such as ours.

4.3 Alternative Explanations

We interpret our results as evidence that the expansion of children's internet usage in Brazil had no effects on test scores. Given that 3G coverage did translate into greater use of mobile internet in Brazil (Section 3), there are at least two alternative explanations for our empirical results: (1) adults access mobile internet, but children do not; or (2) in early years, adoption rates were too low for us to detect effects on the population average when we aggregate across years.

Children's access to mobile internet

One concern might be that the increase in internet use during our study period was concentrated among adults, and that children were largely unable to access the internet. However, mobile internet coverage extended internet use to children and adolescents as well. The vertical axis of Figure A.5 plots the share of children and adolescents in using the internet in a representative sample of each of the five regions in Brazil.[14] The x-axis shows the share of municipalities covered by 3G in each region. In 2015, the earliest survey which asked this question, at least 54% and 70% of children in the North and Northeast regions, the poorest in the country, used internet in the past 30 days. In the richest regions, children's internet usage varied between 80% and 90%. One limitation is

[13]The TWFE regression allows us to estimate one more lag and lead of treatment than the robust difference-in-differences estimator proposed by de Chaisemartin and D'Haultfœuille (2020) because it does not require a not-yet-treated group in every time period.

[14]Source: CETIC.

that this survey does not distinguish between mobile and computer-based internet; however, given that home computers are far less common than smartphones in Brazil during this time period, we expect that most of this reported internet use is mobile-based.

Low 3G adoption rates in early years of study period

It is possible that we find no effects of 3G because our empirical strategy aggregates over multiple years in which 3G usage was modest. Even though 3G coverage and access increases throughout the entire study period (2008-2016), subscriptions per capita only cross the 50% mark and rapidly increase to over 80% of the population after 2014 (Figure A.2). Moreover, we only have data on children and adolescents' internet usage from 2015 onward. To investigate this possibility, we estimate the effects of 3G restricting our observations to later years when there was higher mobile internet usage (2013 and 2015).[15]

We find no evidence of an impact of 3G on education even in high-usage years. Table 1 shows that when examining only 2013 and 2015, the effect of 3G is zero for both Portuguese and math, be it aggregating grades in Columns (4) and (7), or distinguishing between 5th and 9th grades in Columns (5)-(6) and (8)-(9). Because restricting to 2013 and 2015 reduces the number of years after 3G entry that we can observe, we estimate only short-term effects (0-2 years after adoption). We again are well powered to find effects: at 80% power, we can reject effects as small as 0.024SD for Portuguese (Column 4) and 0.028SD for math (Column 7) at the 95% significance level.

5 Discussion

This paper studies the entry of 3G mobile internet into Brazil and finds that 3G coverage had precisely zero effect on test scores, despite increased mobile internet usage among both adults and children. To put the intensity of treatment in context, other papers in the literature have found positive effects of broadband internet on other outcomes with similar or lower levels of penetration. In the same setting as ours, Bessone et al. (2020) find that politicians react to the expansion of 3G internet by increasing social media engagement with municipalities while transferring fewer federal resources to them. In Nigeria and Senegal, in spite of less widespread internet usage, Bahia et al. (2020) and Masaki et al. (2020), respectively, 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

[15] We use the robust difference-in-differences estimator from Section 4.1.1.

20% of individuals report using internet weekly. These previous results suggest that the level of 3G penetration in our sample should be enough to detect effects on educational outcomes if there were any. However, we can rule out small positive or negative effects of mobile internet on test scores.

Although advocates for building internet infrastructure often cite positive effects on education as a justification for government investment, the net effect of mobile internet was a priori ambiguous. Provision of 3G internet could have had a positive impact on children's learning if it increased access to better school materials or labor market opportunities. However, 3G internet could have had a negative impact if internet-enabled leisure activities distracted from schoolwork. Overall, mobile internet was neither the positive transformative force that some hoped for, nor as disastrous as others (mostly speaking about high-income countries) predicted.[16] Based on these findings, given that an increasing number of children spend hours on their phones every day, connected to the internet, it may be valuable to invest in future research to understand what policymakers and educators can do to build on internet connectivity to improve children's learning.

[16] Example news articles (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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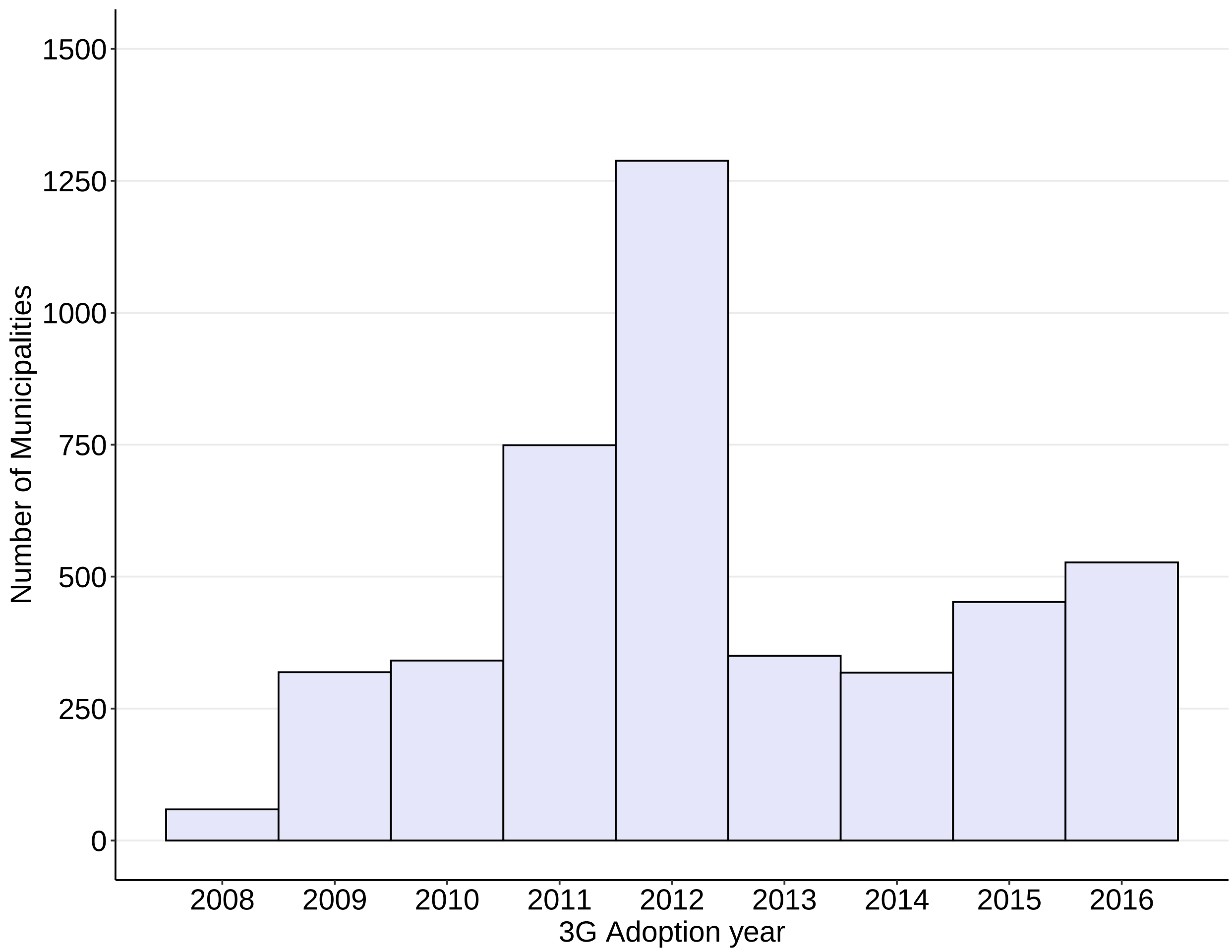
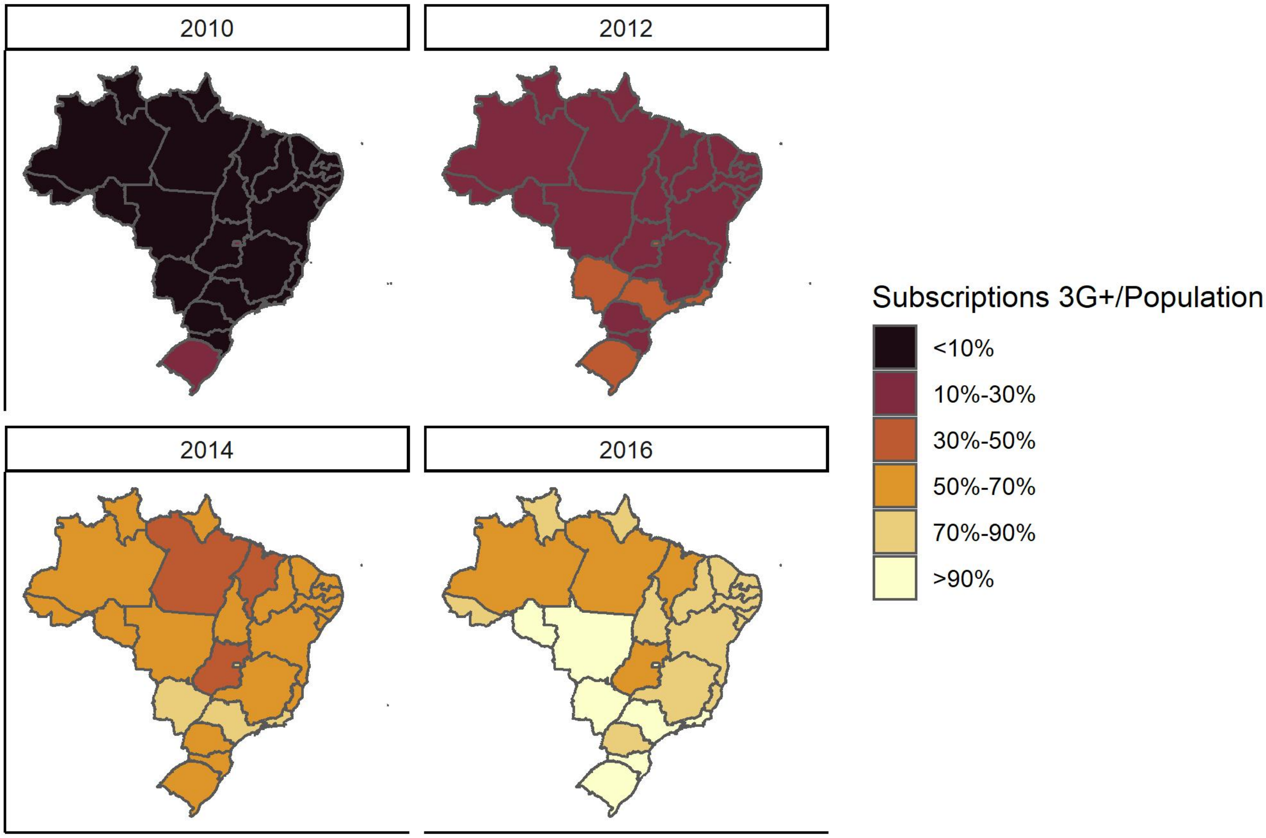
Main Exhibits

Figure 1: Staggered Adoption of 3G Mobile Internet by Brazilian Municipalities



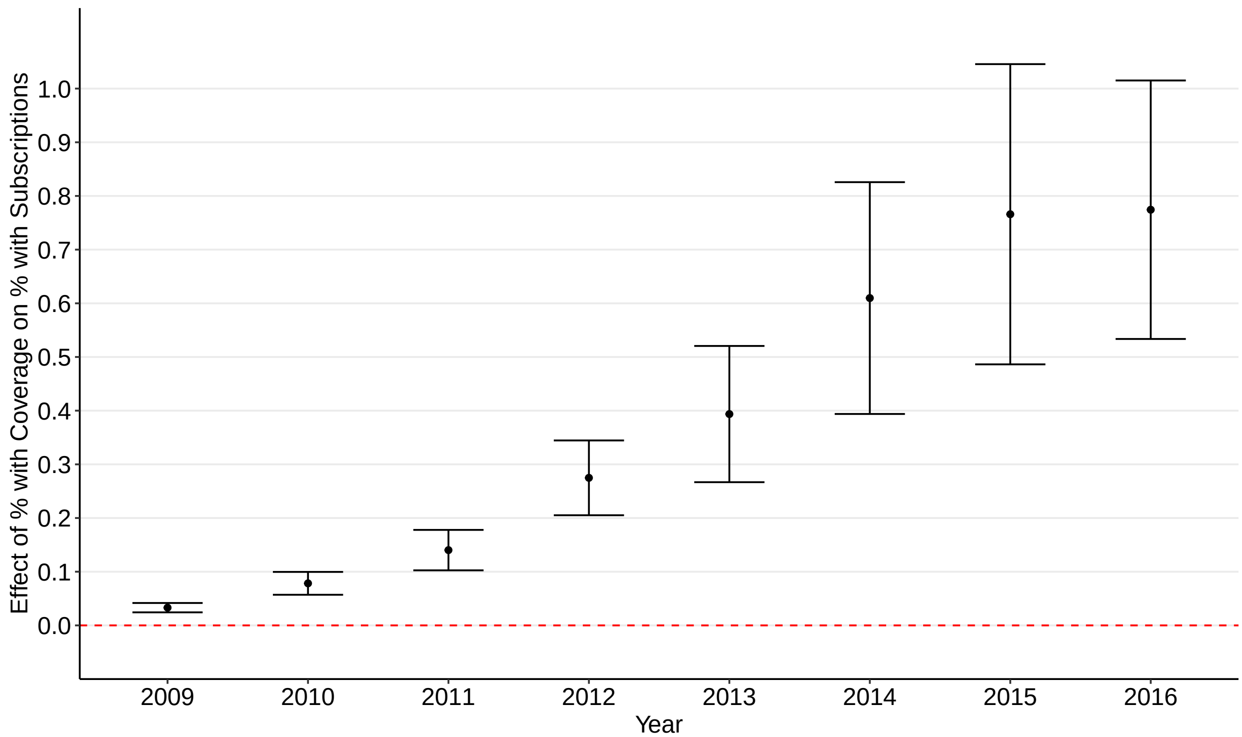
Note: This histogram displays the timing of 3G entry into municipalities in our study sample. The study sample includes the 4403 municipalities which reported Prova Brasil test scores for every exam between 2007 and 2016, and which were treated with 3G between October 2008 and June 2016, which is the time period for which Teleco provided us with 3G adoption data. There are 5570 municipalities in total in Brazil, so this sample consists of approximately 80% of all Brazilian municipalities. 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 be consistent with our main outcome variable, scores on the Prova Brasil exam, which is administered in November.

Figure 2: Evolution of 3G usage by state



Note: These maps show the penetration of mobile broadband internet subscriptions at the state level obtained from the Brazilian National Telecommunications Agency (ANATEL) for 2010 through 2016. Subscriptions are measured as the number of mobile devices with access to 3G or 4G internet plans. Darker colors indicate a lower penetration of 3G subscriptions per person. These graphs demonstrate that in 2010, fewer than 10% of the population in all but two states had subscribed to 3G/4G services. However, by the end of our study period in 2016, all municipalities had at least 0.5 mobile internet subscriptions per capita.

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

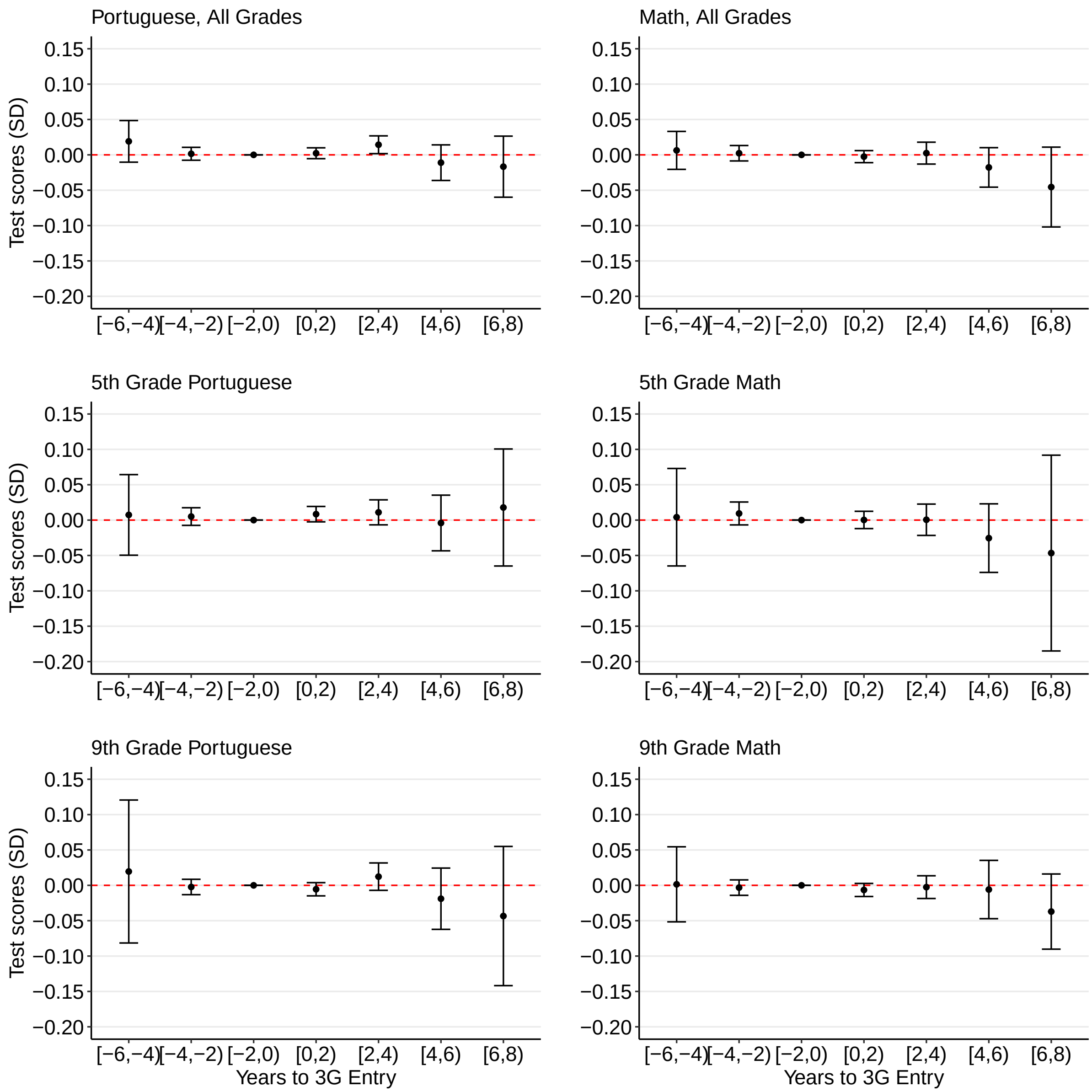


Note: This figure shows how 3G coverage translates into mobile internet subscriptions during our study period by plotting the β_t estimates from the regression

$$\text{share\_with\_subscriptions}_{it} = \sum_{t'=2009}^{2016} \beta_{t'} \mathbb{1}\{t = t'\} \text{ share\_with\_coverage}_{it} + \delta_t + \varepsilon_{it}$$

where increasing the share of the population with 3G coverage during year t by 1 percentage point increases the share of the population with a 3G subscription by β_t. The variable $\texttt{share\_with\_subscriptions}_{it}$ is the number of mobile internet (3G or 4G) subscriptions divided by the population in DDD region i at year t. The variable $\texttt{share\_with\_coverage}_{it}$ is the fraction of the population in DDD region i living in municipalities with 3G coverage during year t. We include time fixed effects δ_t in the regression to capture any increase in mobile internet subscriptions that is not associated with an increase in the number of municipalities covered with 3G (i.e. to exclude from β_t any increases in subscriptions due to greater adoption over time within municipalities which already had 3G coverage). This analysis is run at the DDD level because DDD regions are the lowest level of geographic aggregation for which data on 3G/4G subscriptions were available. The whiskers represent 95% confidence intervals, with standard errors clustered at the DDD region level.

Figure 4: Dynamic Effects of Mobile Internet on Test Scores (Robust DID Estimator)



Note: This figure shows estimated effects of 3G mobile internet on test scores using the robust differences-in-differences estimator (de Chaisemartin and D'Haultfœuille, 2020) discussed in Section 4.2. The outcomes of interest are student-level Portuguese and math scores on the 2007, 2009, 2011, 2013, and 2015 Prova Brasil exams, standardized against the 1997 exam by the *Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira* (Inep) to ensure compatibility across exam years. The reported coefficients show the time path of test scores relative to the time period before 3G adoption, which is normalized to zero. The treatment date for each municipality is obtained from Teleco, a telecommunications consultancy firm, and is defined by the date at which the first cellphone operator began to offer 3G commercially in that municipality. In these event studies, we include municipalities which were treated with 3G between October 2008 and June 2016, which is the time period for which Teleco provided us with 3G adoption data. All reported regressions include state-by-year and municipality fixed effects. The bars represent 95% confidence intervals with standard errors clustered at the municipality level.

Table 1: Effect of 3G on Student Test Scores - Later Years

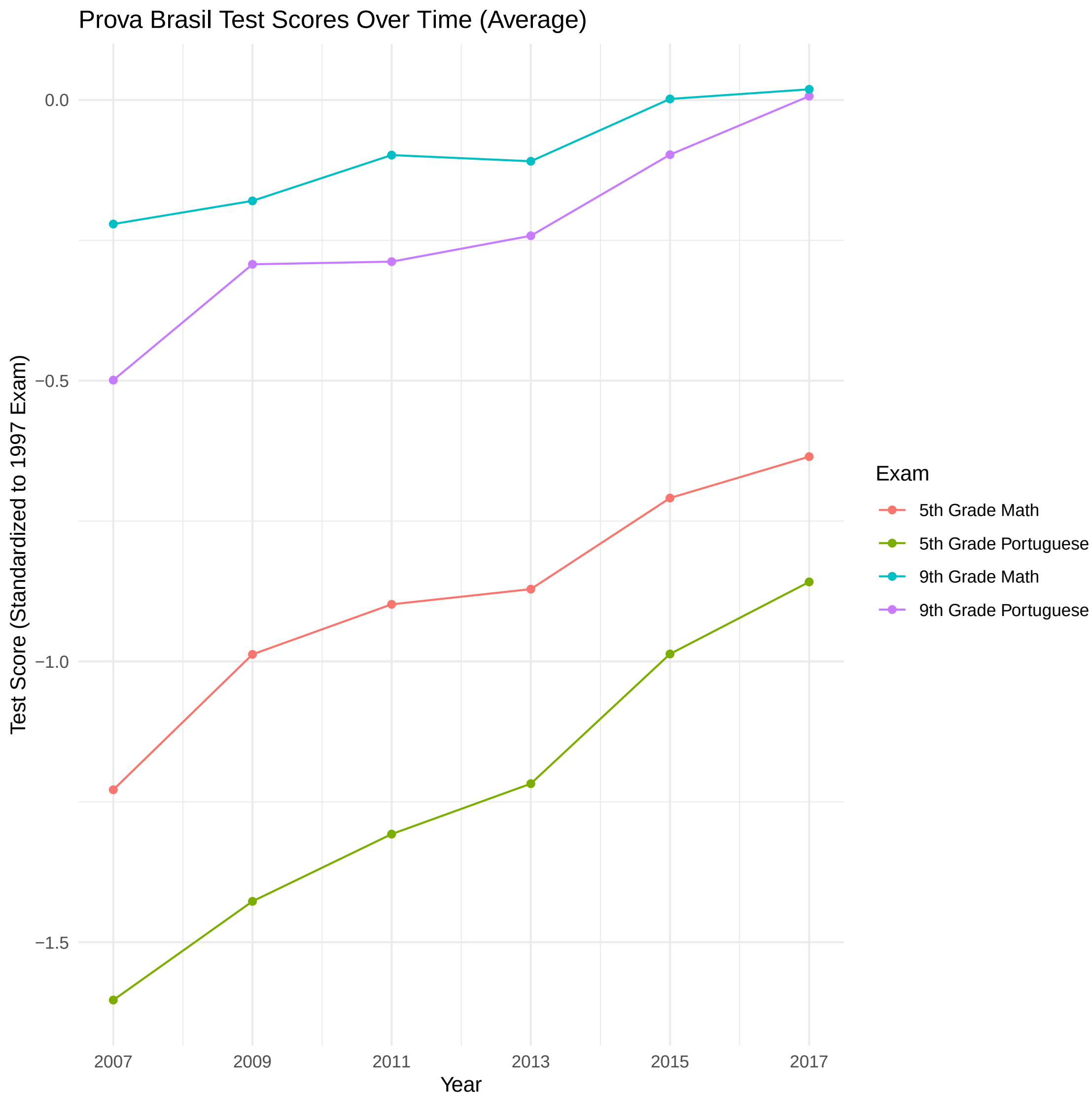
	All Subjects			Portuguese			Math		
	All Grades	Grade 5	Grade 9	All Grades	Grade 5	Grade 9	All Grades	Grade 5	Grade 9
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Instantaneous Effect	-0.003	0.005	-0.001	0.001	0.008	-0.009	-0.006	-0.008	-0.010
	(0.015)	(0.019)	(0.015)	(0.008)	(0.011)	(0.010)	(0.010)	(0.014)	(0.010)
	[0.853]	[0.770]	[0.937]	[0.920]	[0.464]	[0.359]	[0.520]	[0.576]	[0.336]
Observations	605204	321876	280120	2349616	1222612	1123626	2349616	1222612	1123626

Note: This table shows estimated effects of 3G mobile internet based on the robust instantaneous differences-in-differences estimator (de Chaisemartin and D'Haultfœuille, 2020) discussed in Section 4.3. To address the concern that low usage of 3G at the beginning of our study period may attenuate estimates which use the entire 2008-2016 time-frame, this table reports regression results using only exams from 2013 and 2015, ensuring that 3G usage was high in treated municipalities at the time of the exams (see Figure 2). The outcomes of interest are Portuguese and math scores on the Prova Brasil, a nationwide exam administered every other year to 5th and 9th grade students. The point estimates represent the impact of 3G adoption on Prova Brasil scores within 2 years of 3G treatment. All reported regressions include state-by-year and municipality fixed effects. Standard errors clustered at the municipality level are presented in parentheses ( ). P-values are presented in square brackets [ ].

Online Appendix

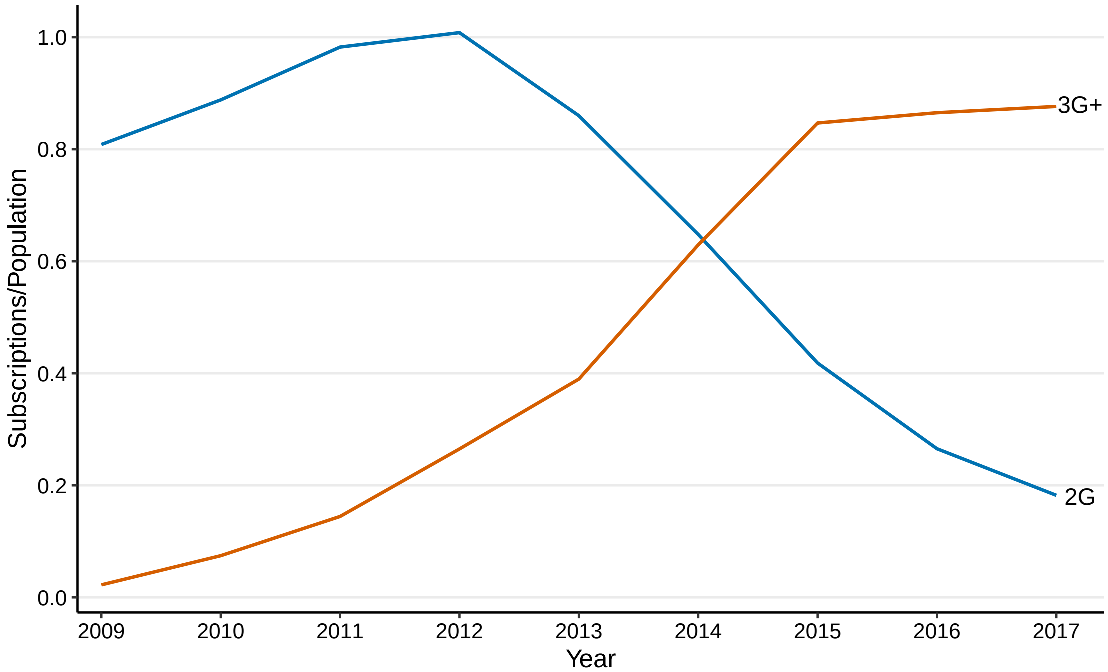
A Figures and Tables

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



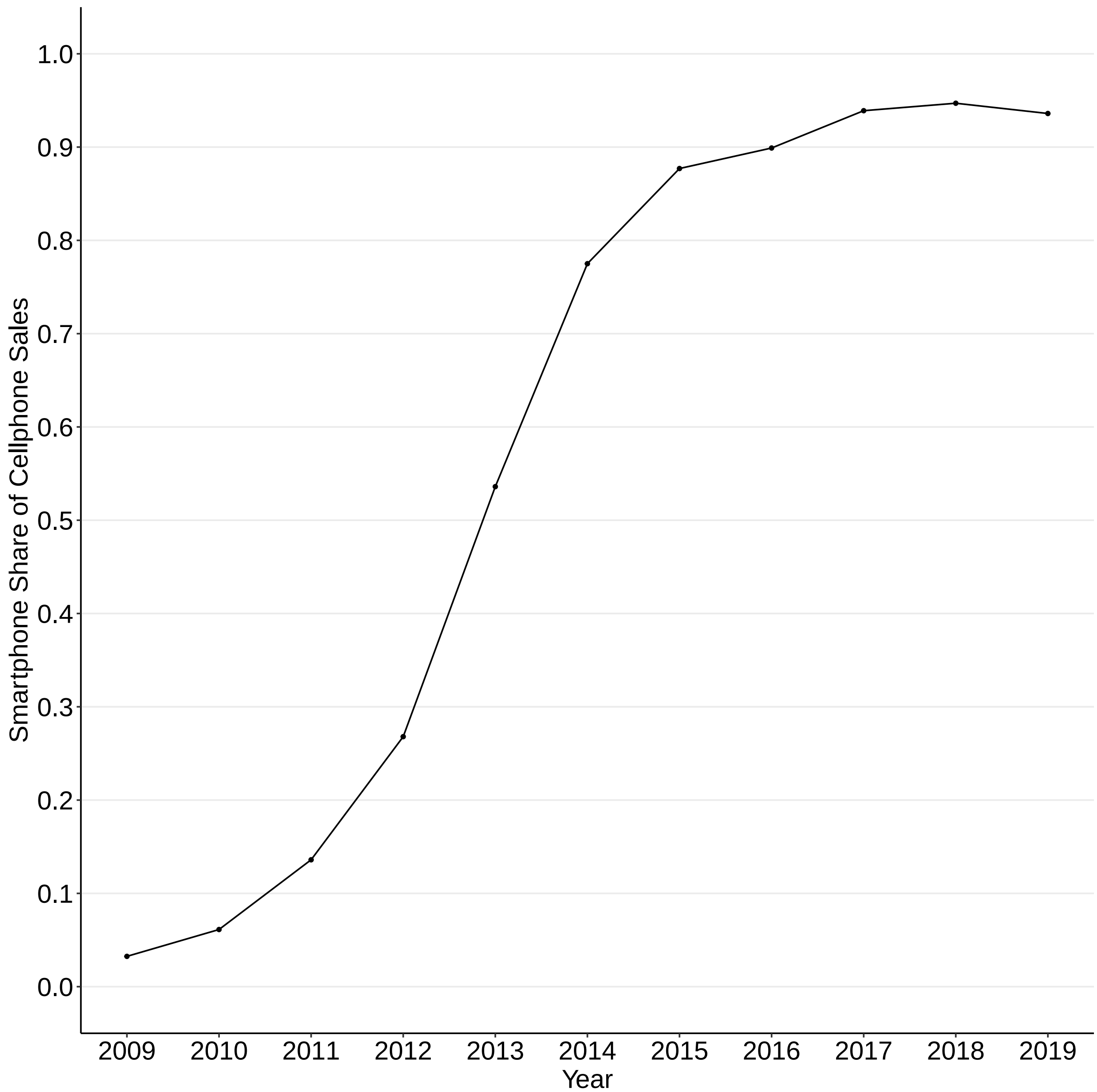
Note: This figure shows the evolution of 2G (blue) and 3G/4G (orange) internet penetration (subscriptions/population) in Brazil between 2009 and 2017. Subscriptions are measured as the number of devices with access to 2G, 3G and 4G internet plans (ANATEL). The penetration of 2G went from 100% at its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

Table A.1: Municipality Characteristics by 3G Adoption Year

3G Adoption Year	Cohort Size	Income Per Capita	Electricity (%)	Urban (%)	Portuguese Score	Math Score
Before 2008	304	303.507	0.968	0.912	-0.842	-0.581
2008	136	297.596	0.959	0.892	-0.771	-0.49
2009	268	198.512	0.928	0.74	-0.931	-0.644
2010	572	206.857	0.914	0.673	-0.859	-0.564
2011	1330	187.181	0.888	0.62	-0.851	-0.527
2012	662	158.424	0.834	0.551	-0.934	-0.615
2013	223	141.749	0.822	0.601	-1.067	-0.789
2014	385	137.077	0.868	0.569	-1.004	-0.694
2015	538	134.273	0.813	0.49	-0.994	-0.684
2016	377	112.574	0.735	0.488	-1.098	-0.804
After 2016	703	119.689	0.767	0.487	-1.042	-0.735

Note: Descriptive statistics of municipalities in Brazil by the year in which they received 3G. Dates of 3G entry for each municipality are obtained from Teleco, a telecommunications consultancy firm in Brazil that gathers information from all cellphone operators in the country. The date of 3G adoption is defined as the year in which the first operator started to offer 3G comercially for consumers in that municipality. Cohort size is the number of municipalities which received 3G in the given adoption year. Average income per capita, electrification, and urbanity in each municipality are calculated from the 2000 census. Average income per capita is reported in Brazilian Reals, and electrification and urbanity are reported as percentage of households. Portuguese and math scores are from the 2007 Prova Brasil exam, and are calculated as the average across municipalities in each cohort. The reported scores have been standardized against the 1997 exam by the *Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira* (Inep) in order to make the scores comparable across exam years.

Figure A.3: Smartphones' Share of Cellphone Sales Over Time



Note: This graph plots the share of cellphone sales in Brazil which were smartphones over time. The sales data are acquired from Teleco, a Brazilian telecommunications consultancy company which collects data on the telecom market in Brazil. In 2009, there were approximately 860,000 smartphones sold in comparison to 25.6 million "dumb" cellphones. By the end of our sample in 2016, smartphones had 89% of the cellphone market. 43.5 million smartphones were sold in comparison to 5 million "dumb" phones.

Table A.2: Effects of 3G on Student Test Scores

	All Grades		Grade 5		Grade 9	
	Portuguese	Math	Portuguese	Math	Portuguese	Math
	(1)	(2)	(3)	(4)	(5)	(6)
4-6 years before	0.019	0.006	0.007	0.004	0.020	0.001
	(0.015)	(0.014)	(0.029)	(0.035)	(0.052)	(0.027)
	[0.203]	[0.645]	[0.801]	[0.908]	[0.704]	[0.957]
2-4 years before	0.002	0.002	0.005	0.009	-0.002	-0.003
	(0.005)	(0.006)	(0.006)	(0.008)	(0.006)	(0.006)
	[0.747]	[0.679]	[0.430]	[0.256]	[0.676]	[0.566]
0-2 years after	0.002	-0.003	0.008	0.000	-0.006	-0.007
	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)
	[0.559]	[0.562]	[0.129]	[0.972]	[0.244]	[0.166]
2-4 years after	0.014	0.002	0.011	0.000	0.012	-0.003
	(0.006)	(0.008)	(0.009)	(0.011)	(0.010)	(0.008)
	[0.026]	[0.758]	[0.224]	[0.965]	[0.213]	[0.757]
4-6 years after	-0.011	-0.018	-0.004	-0.025	-0.019	-0.006
	(0.013)	(0.014)	(0.020)	(0.025)	(0.022)	(0.021)
	[0.390]	[0.213]	[0.839]	[0.303]	[0.392]	[0.778]
6-8 years after	-0.017	-0.046	0.018	-0.047	-0.043	-0.037
	(0.022)	(0.029)	(0.042)	(0.071)	(0.050)	(0.027)
	[0.448]	[0.114]	[0.673]	[0.509]	[0.387]	[0.171]

Note: This table shows estimated effects of 3G mobile internet based on the robust differences-in-differences estimator (de Chaisemartin and D'Haultfœuille, 2020) discussed in Section 4.2. The outcomes of interest are Portuguese and math scores on the Prova Brasil, a nationwide exam administered every other year to 5th and 9th grade students. In these event study regressions, the dependent variable is student-level scores from the 2007, 2009, 2011, 2013, and 2015 Prova Brasil exams, standardized against the 1997 exam by the *Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira* (Inep) to ensure compatibility across exam years. The reported coefficients show the time path of test scores relative to the time period before 3G adoption, which is excluded in our regressions. The treatment date for each municipality is obtained from Teleco, a telecommunications consultancy firm, and is defined by the date at which the first cellphone operator began to offer 3G commercially in that municipality. In these event study regressions, we include municipalities which were treated with 3G between October 2008 and June 2016, which is the time period for which Teleco provided us with 3G adoption data. All reported regressions include state-by-year and municipality fixed effects. Standard errors clustered at the municipality level are presented in parentheses ( ). P-values are presented in square brackets [ ].

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

	5th Grade		9th Grade	
	Portuguese	Math	Portuguese	Math
	(1)	(2)	(3)	(4)
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 the two-way fixed effects regression studying the effect of 3G coverage on students' exam scores in Brazil. 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.

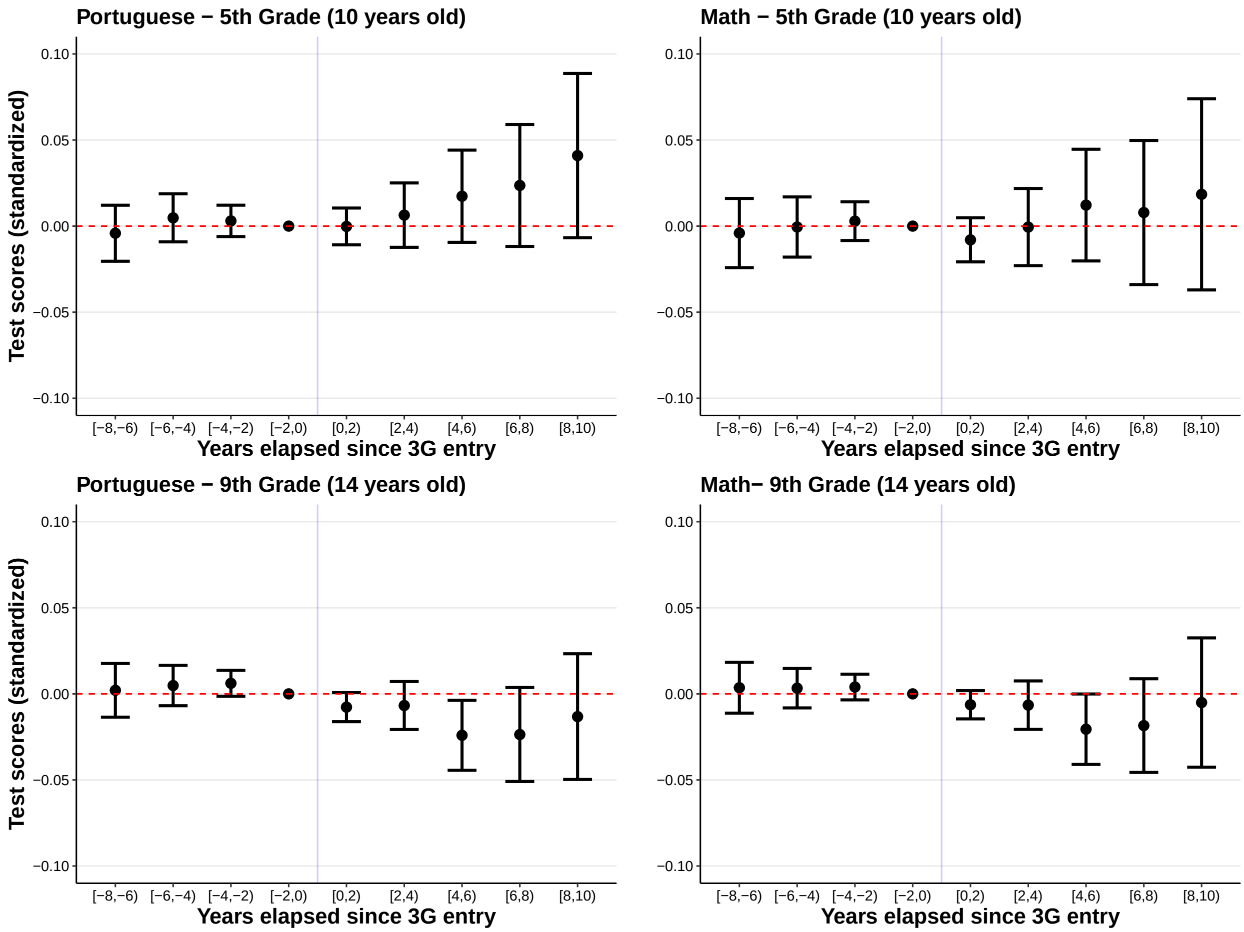
Table A.4: Summary Measures of Two-Way Fixed Effects Regressions' Robustness to Heterogeneous Treatment Effects

	Portuguese			Math		
	All Grades	Grade 5	Grade 9	All Grades	Grade 5	Grade 9
Panel A: Weights on the group/time TE's						
Number of group/time TE's in weighted sum	13,231	13,085	13,091	13,231	13,085	13,091
With positive weight	10,640	10,568	10,326	10,640	10,565	10,325
With negative weight	2,591	2,517	2,765	2,591	2,520	2,766
Sum of weights:	1.000	1.000	1.000	1.000	1.000	1.000
Positive	1.380	1.378	1.385	1.380	1.380	1.385
Negative	-0.380	-0.378	-0.385	-0.380	-0.380	-0.385
Panel B: Robustness to TE Heterogeneity						
Min SD of TE compatible with DGP where ATT is different sign from β	0.00060	0.00312	0.00420	0.00206	0.00143	0.00384
Min SD of TE compatible with DGP where group/time TE's are all different sign from β	0.00124	0.00000	0.00863	0.00424	0.00294	0.00790

Note: This table describes the composition of the standard two-way fixed effects regressions of test scores of entry of 3G mobile internet under the parallel trends assumption. Recent papers in the econometrics literature show that estimated treatment effects from the standard two-way fixed effects regression can be written as the weighted sum of conditional average treatment effects, and that these weights are sometimes negative (de Chaisemartin and D'Haultfœuille, 2020; Callaway and Sant'Anna, 2020; Abraham and Sun, 2020; Goodman-Bacon, 2020; Borusyak and Jaravel, 2017). Under treatment effect homogeneity, negative weights are not problematic; the weights always add up to one, and so any negatively weighted treatment effects cancel out with positively weighted treatment effects if the treatment effects are homogenous. However, if treatment effects are heterogeneous, then the estimated coefficient from the two-way fixed effects estimator may not be economically meaningful, and may in fact be differently signed from the group-time treatment effects. In this table, we report statistics proposed by de Chaisemartin and D'Haultfœuille (2020) and computed using the Stata package `twowayfeweights`, which shed light on whether heterogeneity in treatment effects poses a problem to the standard two-way fixed effects regression in our setting.

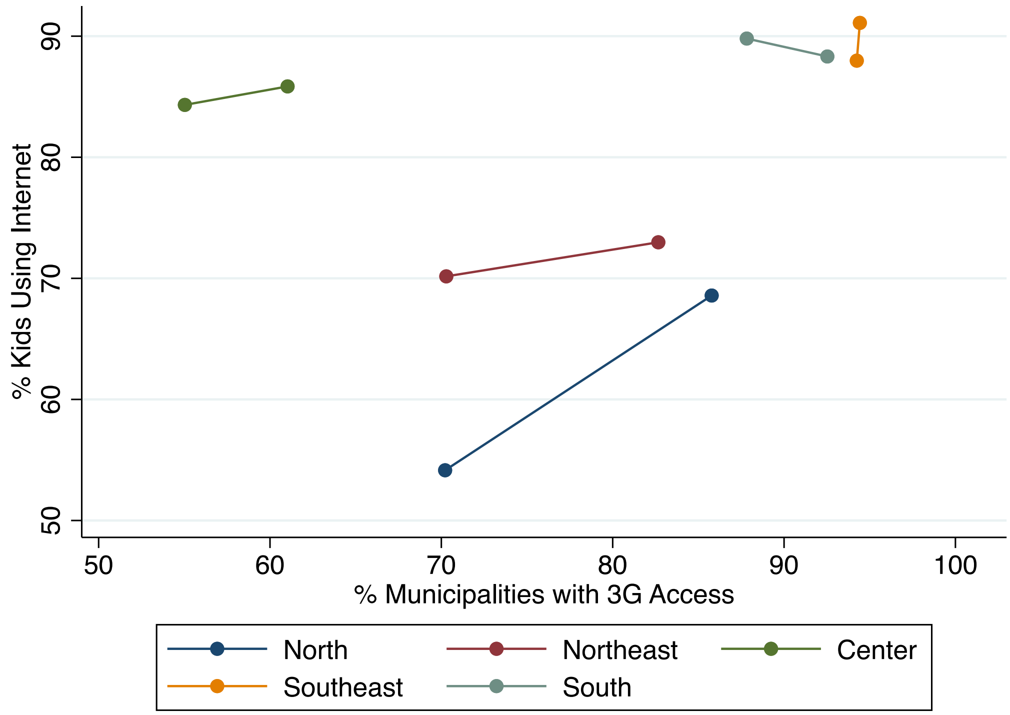
Panel A describes the group-time treatment effects which are inpurs into the weighted sum which gives us the overall treatment effect. Across all regressions, we see that 20-25% of these group-time treatment effects have negative weights, and that the sum of those negative weights is approximately -0.38. *Panel B* describes the minimum heterogeneity in treatment effects which would be required for the coefficient β from the standard two-way fixed effects regression to be differently signed from the group-time treatment effects. The first summary statistic is the minimal value of the standard deviation of the treatment effect across treated group and time periods under which the average group-time treatment effect would be differently signed from β; this ranges from 0.00060 to 0.00420. The second summary statistic if the minimal value of the standard deviation of the treatment effect across treated groups and time periods under which all group-time treatment effects could be differently signed from β; this range from 0 to 0.00863. These robustness measures show that very small amounts of treatment effects heterogeneity are required for the two-way fixed effects regression coefficient to be incorrectly signed in our context, and so we use a heterogeneity-robust difference-in-differences estimator in our main results.

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



Note: These graphs plot the estimates from a standard two-way fixed effects event study regression with state×year fixed effects, 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.

Figure A.5: Evolution of 3G Coverage and Internet Usage by Kids 9-17 Years Old



Note: This graph plots the percentage of children aged 9-17 years old using the internet (vertical axis) against the percentage of municipalities covered by 3G (horizontal axis) by region. We obtain these data from The Regional Center for Studies on the Development of the Information Society (CETIC), an arm of the Brazilian Network Information Center, for the years in which these surveys were conducted (2015 and 2016). The survey asks about internet use from any device, including phones, computers, or tablets.

B Details about placebo estimation

$DID^{pl}_{+,t,l}$ compares the time path of outcomes over period $t-2l-2$ to period $t-l-1$ for municipalities which were treated at time period t and those which remained untreated at t. This placebo estimator checks that treated and untreated municipalities were on parallel trends in the $l+1$ periods leading up to time period t.

$$DID^{pl}_{+,t,l} = \sum_{m:3G_m=t-l} \frac{N_{m,t}}{N_t^{t-l}}(Y_{m,t-2l-2} - Y_{m,t-l-1}) - \sum_{m:3G_m>t} \frac{N_{m,t}}{N_t^{NT}}(Y_{m,t-2l-2} - Y_{m,t-l-1}) \tag{B.1}$$

$DID^{pl}_{+,t,l}$ is used as a building block to construct an estimator which aggregates across cohorts. $DID^{pl}_{+,l}$ is the placebo equivalent of $DID_{+,l}$:

$$DID^{pl}_{+,l} = \frac{\sum_{t=2l+3}^{NT} N_t^{t-l} \beta_t DID^{pl}_{+,t,l}}{\sum_{t=2l+3}^{NT} N_t^{t-l} \beta_t} \tag{B.2}$$