3G Internet and Human Capital Development*

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Abstract

We study the impact of global expansions in mobile internet access between 2000 and 2018 on student outcomes. We link geospatial data on the rollout of 3G mobile technology with over 2 million student test scores from 82 countries. Our findings indicate that the introduction of 3G coverage leads to substantial increases in smartphone ownership and internet usage among adolescents. Moreover, changes in 3G coverage are associated with significant declines in test scores across all subjects, with magnitudes roughly equivalent to the loss of one-quarter of a year of learning. We find suggestive evidence that a reduction in feelings of belonging, ease of making friends, and self-efficacy may explain these impacts.

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1 Introduction

In recent years, the rapid proliferation of internet access and advancements in technology have impacted nearly every aspect of children's lives. 95 percent of American teenagers have access to a cell phone; nearly half say they use the internet "almost constantly."[1] Globally, a UNICEF report based on a survey of over 14,000 children across 11 countries found that one in three internet users is a child (UNICEF, 2019). Still, little is known about the effect that these changes in adolescent's behavior and environment have had on their development of skills. Moreover, the answer to this question is ambiguous. On one hand, information technology can broaden access to information and resources that enhance student learning. Conversely, these technologies may have adverse effects on sleep, mental health, and various other facets of students' lives, which could impede their learning and skill development. This study aims to investigate the impact of 3G internet, a mobile network technology that provides wireless internet connectivity, on the human capital development of adolescents.

In particular, we leverage the staggered rollout of 3G technology to investigate the causal impact of 3G internet on student academic performance. We use test score data from over 2 million students from the Programme for International Student Assessment (PISA), a widely recognized international assessment conducted by the Organisation for Economic Co-operation and Development (OECD). PISA assesses the performance of 15-year-old students in reading, mathematics, and science, assessing both the relative and absolute levels of skill development across regions and time. PISA data offer a rich and comprehensive source of information, enabling us to explore the relationship between 3G internet use, technology access, and student test scores over nearly two decades and across multiple countries.

In this context, we find evidence that expansions in 3G are associated with large increases in student technology use. Students living in areas with 3G coverage are 7 percentage points more likely to browse the internet daily, are 12 percentage points more likely to have a smartphone at home, and spend an additional 40 minutes on the internet every day. In turn, 3G expansion is associated with reductions in student test score performance. The magnitude of these reductions—approximately 0.05 to 0.08 standard deviations—is on par with roughly one-quarter of a year of

[1] "Teens, Social Media and Technology 2022," Pew Research Center, August 10, 2022.

schooling. Our results are robust to specifications that account for potential bias in difference-in-differences estimates, and we obtain larger, similarly signed estimates when using lightning frequency and 2G coverage as instruments for growth in 3G coverage. With respect to potential mechanisms, we find suggestive evidence that measures of social connectedness and mental health—namely, ease of making friends and feeling a sense of belonging—worsen after the arrival of 3G.

This study estimates the impact of mobile internet access at a crucial and meaningful point of time during childhood. Internet use among children tends to increase with age as they grow older and gain more independence and access to digital devices (UNICEF, 2019). While younger children, typically in the early elementary school years, may have limited or supervised access to the internet, as children enter middle school, their internet use often expands to social interaction with peers and online gaming. During adolescence (ages 13-18), teenagers often rely on the internet for communication, social networking, entertainment, information gathering, academic purposes, and self-expression through social media. Many of the social media platforms, such as Facebook, also allow children over 13 years to sign up. With this increased internet use and the multi-faceted nature of use by students in the later years, understanding the impact of 3G technology on their test scores and educational outcomes during adolescence becomes especially relevant. Secondary schooling is an important phase in students' academic development and is crucial for their future educational outcomes and career prospects. Therefore, the information contained in PISA results allows us to assess the influence of mobile internet access at this pivotal and significant stage in their development.

This research contributes to two strands of literature: education technology, and more broadly, the effects of the internet. The education technology literature highlights the complex and varying relationship between technology use and academic performance across contexts and types of technology. The closest paper to ours is Bessone et al. (2020), which finds that 3G expansions in Brazil are associated with no significant improvement or decline in student test scores. Conversely, Aker et al. (2012) report the results of a field experiment in Niger, finding that simple mobile phone use increased test scores among adults. Our study distinguishes itself from prior work by using a much larger set of countries and quantifying various aspects of student life—technology use, mental health, homework, and absenteeism—that may be affected by expansions on 3G coverage.

More broadly, home computer use among children has been found to lower academic test scores but they increased computer skills (Fairlie and Robinson, 2013; Malamud and Pop-Eleches, 2011). However, the influence of parental supervision appears to mediate this relationship, emphasizing the role of guidance and support in technology usage.

Results with respect to more targeted education technology interventions similarly yield mixed results. Recent investigations into online education during the COVID-19 pandemic have revealed that it may be a poor substitute for in-person instruction (Agostinelli et al., 2022; Kofoed et al., 2021). However, a remedial technology-aided after-school program led to significant gains in performance in India (Muralidharan et al., 2019). All of these studies, together with the more comprehensive outline of prior research on the impact of education technology in Muralidharan et al. (2019), underscore the importance of considering the nuances of different forms of technological tools and the extent to which they can complement or substitute for traditional forms of learning in different contexts.

The second strand of literature our paper contributes to is the nascent and rapidly growing work examining the socioeconomic and political impacts of the expansion of the internet. In this sphere, previous studies have exploited the staggered expansion of broadband and 3G networks to identify causal effects. Broadband internet usage has been linked to the widening of the mental health gender gap among women aged 17-30 (Golin, 2022; Donati et al., 2022), increased distractions and lowered sleep quality (Billari et al., 2018), reduced social capital (Geraci et al., 2022), alterations in voting behavior (Falck et al., 2014), and shifts in perceptions of migrants (Golin and Romarri, 2022). Regarding 3G internet, recent evidence suggests that it may affect confidence in government (Guriev et al., 2021), potentially lead to the polarization of political views (Melnikov, 2021), and increase labor force participation among women (Chiplunkar and Goldberg, 2022).

We add to both these strands of literature by studying the effects of 3G on human capital development on a global scale using the PISA dataset, which encompasses a diverse range of countries and educational systems. Using this data allows us to examine the impact of 3G internet on student test scores in a global context, and provides a broader understanding of the implications and potential variations across different socio-cultural settings. Through analysis of this data, we aim to contribute to the growing body of research on the effects of internet use on educational outcomes and the impact of technology in education more broadly.

The rest of the paper proceeds as follows. In Section 2 we outline the data, and Section 3 describes our methodology. Section 4 presents our results. Section 5 concludes.

2 Data

2.1 PISA Data

Our main data source is the OECD's Programme for International Student Assessment (PISA). Administered every three years in countries across Europe, Asia, the Americas, and Africa, PISA measures 15-year-olds' reading, mathematics, and science skills.[2] In each country, PISA aims to obtain a sample that is representative of "15-year-old students attending educational institutions in grades 7 and higher."[3] We use student-level PISA data from all seven rounds of testing between 2000 to 2018.[4]

Our main outcomes are test-based measures of student achievement in reading, mathematics, and science. The OECD transforms student scores such that they have a mean of 500 and a standard deviation of 100. We standardize all reported student scores by subtracting 500 and dividing by 100. Tests administered as part of PISA are "not directly linked to the school curriculum," and are meant to test students' "ability to use their reading, mathematics and science knowledge and skills to meet real-life challenges."[5] To allow for comparisons across years, the OECD performs an equating process based, in part, on common test questions between tests in different years.

In addition to measures of student achievement, OECD data includes several additional variables relating to the characteristics of participating students, as well as the characteristics of their families and schools. We capture data on student gender, age, immigration status, parental education, and whether the student's school is public, private and government-dependent, or private and government-independent. We provide a detailed description of the construction of the main variables used in our analyses in Appendix A.

In every PISA round, representatives from participating schools are asked "Which of the following definitions best describes the community in which your school is located?" Eligible responses are village, town, city, or large city. We refer to this variable as urbanicity. We use this

[2] A full list of participant countries can be found at PISA Country List.

[3] PISA 2018 Technical Report, Chapter 4.

[4] In response to the COVID-19 pandemic, the OECD postponed the scheduled PISA 2021 assessment.

[5] What is PISA?, About PISA.

variable, in combination with the geospatial data described below, to capture student exposure to 3G coverage over time. Figure 1 shows the number of responses in each year-by-country-by-urbanicity cell.

To gain insights into students' engagement and their social connectedness and mental well-being within the school context, we additionally consider student homework hours, absenteeism, ease of making friends, sense of belonging, and self-efficacy. Not all of these variables are available for all years and where the scales vary across the years, Appendix A details how we harmonize measures across PISA rounds. In addition, Appendix Figures C.2 to C.6 summarize annual missingness by country-by-urbanicity pair for variables for which full data is not available.

Finally, we capture several student responses to the Information Communication Technology (ICT) questionnaire. This questionnaire is optional among countries participating in PISA and includes a set of survey questions related to students' use of technology, their digital competencies, and their attitudes toward information and communication technologies. Because these questions are not administered to every student in each PISA round, we define two samples in our analysis of PISA data: our "full sample," which includes all student observations for which data is available for our main testing and control variables, and our "ICT sample," which additionally requires that observations have non-missing responses to our main ICT variables. These samples include over 2.2 million and 1.4 million student-level observations, respectively. Appendix Figure C.1 displays the set of country-by-urbanicity pairs that appear in the ICT sample in each PISA round.

2.2 Geospatial Data

As described above, PISA data includes a measure of urbanicity at the school level, which identifies whether each school is located in a village, town, city, or large city. PISA questionnaires define these categories based on population: villages have fewer than 3,000 residents, towns have more than 3,000 but fewer than 100,000, cities have more than 100,000 but fewer than 1,000,000, and large cities have more than 1,000,000. Using a combination of data sources described below, we calculate the share of the population with 3G coverage each year in each country-by-urbanicity cell. Figure 2 illustrates this process in the Czech Republic.

2.2.1 3G Coverage Data

We use data on 3G coverage from Collins Bartholomew. This data ranges from 2007 to 2018, excluding 2010 and 2017. In each year, Collins Bartholomew data comes in the form of shapefiles that indicate which areas of each country have 3G coverage. Panel A of Figure 2 displays this data for 2007, 2012, and 2018 in the Czech Republic. For each year, areas shown in black had 3G coverage and areas shown in grey did not.

2.2.2 Global Population and Urbanicity Data

We use data from the Gridded Population of the World and the Global Human Settlement Layer to identify the area as either a village, town, city, or large city.

Gridded Population of the World data reports population counts and population density for each 2.5 arc-minute point on the earth. We combine this data with the Global Human Settlement Layer's Urban Centre Database to identify points that fall in cities and large cities. Consistent with the definitions used in PISA, We classify any urban center with a population greater than 1,000,000 as a large city, and any urban center with a population larger than 100,000. (Population estimates are as of 2015.[6])

Finally, we use population density data from the Gridded Population of the World to distinguish between towns and villages. We define villages as points with fewer than 100 people per square kilometer. The remaining points—those with more than 100 people per square meter that do not fall in a city or large city—are treated as towns.

Panel B of Figure 2 displays these designations for the Czech Republic, which has one area designated as a "Large City," Prague, and three separate areas designated as "Cities," corresponding to Brno, Ostrava, and Plzeň. The remaining area is split between towns and villages.

2.2.3 Calculating 3G Coverage

For each round of Collins Bartholomew data, we calculate 3G coverage for each country-by-urbanicity pair as the share of points that have 3G, weighted by the total population. Panel C of Figure 2 displays these estimates for the Czech Republic. In the Czech Republic, Prague had

[6]Global Human Settlement Layer's Urban Centre Database provides population estimates as of 1975, 1990, 2000, and 2015.

full 3G coverage since the start of the data series in 2007. Cities, towns, and villages grew from lower levels of 3G coverage in 2007 to nearly full coverage by 2018.

Many areas had non-zero 3G coverage in 2007. For these countries, we identify the month that commercial 3G coverage was introduced in the country, and assume that coverage in the month prior was zero.[7]

With these data, we estimate 3G coverage on a monthly basis for each country-by-urbanicity pair by linearly interpolating between all available measures of 3G coverage. With this monthly data, we calculate the average level of 3G coverage for the 12 months prior to the month in which students completed the PISA examination. We perform the same calculation using data on global 2G coverage (also from Collins Bartholomew) as of 2007, which we use in our instrumental variables estimates.

2.2.4 Lightning Data

In our instrumental variables estimation, we use lightning frequency as an instrument for 3G coverage. Specifically, we use Gridded Lightning Climatology Data available through NASA. This data reports the average lightning flash rate for each point on the earth's 0.5-degree by 0.5-degree latitude-longitude grid. Similar to the 3G calculations above, we calculate each country-by-urbanicity cell's average population-weighted lightning frequency by calculating the lightning frequency for each 2.5 arc-minute point on the earth and weighting these values by each point's total population.

2.3 Data Description

Table 1 displays summary statistics for our sample, separately for our full sample (in Panel A) and our ICT sample (in Panel B). For both samples, roughly half of the students are male and most students are between the ages of 15 and 16. Over the whole panel, which spans from 2000 to 2018, average levels of 3G exposure (as measured by the share of their population with 3G coverage)

[7] These months are as follows: Australia: 10/2002, Austria: 4/2003, Belgium: 4/2004, Brunei: 8/2005, Croatia: 2/2005, Czech Republic: 12/2005, Denmark: 10/2003, Estonia: 10/2005, Finland: 1/2002, France: 5/2004, Germany: 2/2004, Greece: 7/2003, Hong Kong-China: 1/2004, Hungary: 5/2005, Indonesia: 9/2006, Ireland: 5/2003, Israel: 8/2004, Italy: 3/2003, Japan: 10/2001, Korea: 5/2002, Malaysia: 5/2005, Netherlands: 9/2003, New Zealand: 11/2004, Norway: 12/2004, Philippines: 2/2006, Poland: 9/2004, Portugal: 6/2004, Romania: 4/2005, Singapore: 12/2004, Slovak Republic: 1/2006, Slovenia: 12/2003, Sweden: 5/2003, Switzerland: 11/2004, Taiwan: 5/2005, United Kingdom: 3/2003, United States: 1/2002.

are roughly 0.58. This figure is larger—0.62—for the ICT sample in Panel B.

Both panels additionally summarize a set of variables related to homework, attendance, social connectedness, and mental well-being. As noted above, these questions were not administered universally across countries and PISA rounds; Appendix Figures C.2 to C.6 summarize annual missingness by country-by-urbanicity pair for variables for which full data is not available.

Panel B additionally summarizes measures of technology access and use. 53 percent of interviewed students browse the internet daily. Among students interviewed in 2012, 2015, and 2018, 90 percent had a smartphone at home and the average daily number of minutes spent on the internet was 250, about 4 hours.

ICT measures that capture access to and use of technology change substantially over the course of our sample. To illustrate this phenomenon, Figure 3 shows over-time trends among PISA countries for 3G coverage as well as other measures of technology access and use. To construct the figure, we calculated country-level averages of each variable in each year, weighted by PISA sampling weights. Grey points in Figure 3 reflect these country-level averages, while black lines reflect the average country-level values in each year.

All measures of technology use and access in Figure 3 exhibit large increases between 2000 and 2018. Notably, trends in 3G coverage closely mirror the trends in smartphone ownership and internet browsing frequency.

Establishing a causal link between technology use and test scores is challenging not only due to selection bias but also because the observational patterns differ across different measures of technology use. To illustrate this point, Table 2 displays the observed relationship between test scores and various measures of technology use in PISA data from 2012, 2015, and 2018. We use three measures of technology use: average daily internet use, smartphone ownership, and an indicator variable for students who browse the internet daily. Across all subjects, students who spend more time using the internet score lower on PISA exams; coefficient estimates in Column 1 suggest that a one-hour increase in daily internet use is associated with a 0.03 standard deviation reduction in PISA scores. By contrast, the other two measures we evaluate—smartphone ownership and daily internet browsing—exhibit positive associations with test scores across all subjects. These contrasting results hold when all measures are used simultaneously in Column 4.

Our methodology, described in the section below, aims to establish a causal link between

3G coverage and student skills and behavior. To do so, we leverage the global expansion in 3G coverage between 2000 and 2018 and assess the relationship between local 3G availability and student technology use, test scores, and behavior.

3 Methodology

3.1 Difference-in-Differences

To measure the effect of 3G coverage on student-level outcomes, we use a difference-in-differences specification that compares trends in test scores across areas with and without 3G coverage over time. Our baseline two-way fixed effects specification is below.

$$y_{icut} = \gamma 3G_{cut} + X_{icut}\theta + \phi_{cu} + \tau_t + \varepsilon_{icut} \tag{1}$$

where i indexes students, c indexes countries, u indicates urbanicity, and t indexes years. We include fixed effects for country-by-urbanicity and time (ϕ_{cu} and τ_t, respectively), so our estimates reflect differences within areas over time, rather than differences between areas that precede the arrival of 3G. In some specifications, we additionally include country-by-year fixed effects, which means that our estimates reflect within-country-year differences in test scores.

Our set of baseline controls, X_{icut}, include student gender, age, and immigration status, and whether the student's school is public, private with government funding, or private without government funding. Additionally, we control for differential trends based on each country's level of development by interacting 2000 GDP per capita with a time trend. In some specifications, we additionally interact student-level controls with country-by-urbanicity, allowing the effect of each variable to vary across different areas.

Our coefficient of interest, γ, reflects comparisons in trends between areas that received 3G relatively earlier or later than others. Identification in this context relies on the parallel trends assumption that absent the arrival of 3G, treated areas would have followed the same trend as untreated areas.

Recently, many researchers have drawn attention to potential bias that arises in estimating two-way fixed effects models in the presence of staggered treatment and treatment effect heterogeneity (e.g. Goodman-Bacon (2021); Sun and Abraham (2021); De Chaisemartin and d'Haultfoeuille

(2020); Gardner et al. (2023)). In these settings, the use of two-way fixed effects models entails using already-treated units as controls for newly-treated ones, which generates bias if treatment effects vary over time.

To ensure that our main results are not driven by biases arising in two-way fixed effects estimation, we estimate the two-stage difference-in-differences estimator proposed by Gardner et al. (2023). This estimator avoids comparisons between already-treated units and newly treated ones via a two-stage procedure. In the first stage, untreated units are used to estimate group and period effects. In the second stage, treatment effects are estimated by comparing treated and untreated units after removing these group and period effects. This procedure allows for the use of covariates, is computationally efficient, and allows for event-study as well as static treatment effect estimates. We describe our procedure and accompanying results in more detail in Appendix B.

3.2 Instrumental Variables Estimates

In addition to our difference-in-differences estimates, we use instrumental variables estimation to estimate the effect of 3G coverage on student achievement. In these specifications, we use two instruments for 3G coverage: local lightning strike frequency and 2G coverage as of 2007. Manacorda and Tesei (2020) first used lightning strike frequency as an instrument for 3G coverage. Since then, it has since been used much more broadly (Chiplunkar and Goldberg, 2022; Guriev et al., 2021; Jiang et al., 2022). Electrical surges caused by frequent lightning strikes increase the cost of installing and maintaining 3G equipment. Thus, ceteris paribus, areas with more frequent lightning strikes exhibited slower diffusion of 3G availability. Oppositely, prior 2G coverage has been associated with faster expansion of 3G coverage (Harm Adema et al., 2022). Prior infrastructure for 2G can be repurposed or shared with 3G infrastructure. Specifically, cell towers used for 2G can be shared by a 3G base transceiver station. Thus, the expansion of 3G coverage was less costly in areas with preexisting 2G coverage.

We operationalize these observations by multiplying each area's population-weighted lightning frequency, $Lightning_{cu}$, with a time trend t. Similarly, we use 2007 as our base year for constructing 2G coverage, and interact this measure, $2G^{2007}$, with a time trend t. The first-stage equation is below.

$$3G_{cut} = \delta_1[Lightning_{cu} \times t] + \delta_2[2G_{cu}^{2007} \times t] + X_{icut}\mu + \phi_{cu} + \tau_t + \varepsilon_{icut} \tag{2}$$

Here, δ_1 captures the differential rate of 3G availability between areas with relatively higher versus relatively lower levels of lightning frequency. If areas with more lightning exhibited slower diffusion of 3G availability, δ_1 should be negative. Oppositely, δ_2 captures the differential rate of 3G availability between areas with relatively higher versus relatively lower levels of 2007 2G coverage. If areas with more 2G coverage in 2007 exhibited faster diffusion of 3G availability, δ_2 should be positive.

Throughout, we cluster standard errors at the country-by-urbanicity level. In addition, to account for PISA's sampling regime, we weight each observation by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c.

4 Results

In this section, we first explore the relationship between 3G availability and technology access and use among adolescents. Then, we investigate how changes in 3G affect student test scores in math, reading, and science. We also test for heterogeneous effects across different groups of students as well as effects on other aspects of students' lives. For all sets of outcomes, we describe results using difference-in-differences as well as instrumental variables strategies described above.

4.1 Effects on Technology Access and Use

Table 3 shows OLS estimates of the effect of 3G coverage on technology access and use. These results are limited to our ICT sample, which includes roughly 1.4 million student-level observations, slightly more than half of our full sample. Throughout, Columns 1 through 4 vary in the set of control variables used: all specifications include country-by-urbanicity fixed effects, year fixed effects, and baseline controls. Columns 2 and 4 add country-by-year fixed effects, and Columns 3 and 4 interact all baseline controls with country-by-urbanicity fixed effects.

Panel A of Table 3 reports effects on the likelihood that students report browsing the internet daily. Estimates indicate that 3G coverage is associated with a 4 to 7 percentage-point increase in the likelihood of daily internet browsing. These estimates are marginally significant and slightly smaller for regressions excluding country-by-year fixed effects but are larger and highly significant for regressions that include them.

Panels B and C of Table 3 show estimates of the effect of 3G on smartphone ownership. The PISA ICT questionnaire included questions about smartphone ownership starting in 2012. We test for effects on smartphone ownership in two ways. First, we exclude observations prior to 2012 (for which there are no responses). These results, shown in Panel C, are very imprecise and statistically insignificant, but point estimates suggest that 3G coverage increases smartphone ownership between 0 and 5 percentage points.

These estimates omit data prior to 2012, the period in which most 3G expansions occurred. To allow us to include this data, we alternatively estimate the effects on smartphone ownership after assuming that none of the students participating in 2000 and 2003 had a smartphone. These estimates, shown in Panel D, are much larger and suggest that 3G coverage increases smartphone ownership by roughly 7 to 11 percentage points.

Finally, Panel E of Table 3 shows estimates on daily internet use, limiting the sample to the years for which this data is available: 2012, 2015, and 2018. Consistent with the effects described above, access to 3G increases the amount of time students spend on the internet. Effect sizes are reasonably large across specifications, suggesting that 3G coverage increases time on the internet by 30 to 40 minutes daily.

In Appendix B, we repeat these analyses using the two-stage difference-in-differences estimator proposed by Gardner et al. (2023). For effects on smartphone ownership and browsing frequency, we obtain similar results when using this estimator. Due to the limited data availability, we are unable to estimate effects on the length of daily internet use using this method.

In Appendix Table C.1, we show results using our instrumental variables methodology. Due to the smaller size of our ICT sample, and the limited availability of some variables, the standard errors of our estimates are quite large. Still, we document positive and statistically significant effects on smartphone ownership using this approach. Effects on other measures of internet use are noisily estimated, but generally consistent with the OLS results described above.

Overall, these results suggest that 3G coverage accelerated ownership of smartphones and, in turn, the use of the internet. Next, we consider the effect of 3G access on human capital development, as measured by PISA test scores.

4.2 Effects on PISA Test Scores

4.2.1 Main Results

Table 4 shows OLS estimates of the effect of 3G on test scores in reading, math, and science. Similar to the results in Table 3, Columns 1 through 4 report effects with varying sets of controls and fixed effects. Panels A, B, and C report effects on math, reading, and science scores, respectively.

Across all specifications in all subjects, the estimated effects of 3G access on test scores are negative. The statistical significance of these results varies across specifications, but effect sizes are between 0 and 0.1 student standard deviations.

In Appendix B, we show we obtain similar results when we use an estimator that is robust to potential bias associated with two-way fixed effects estimation. These estimates allow us to estimate event studies, which allow us to show estimated treatment effects as a function of years since treatment. Importantly, these estimates do not exhibit pre-trends in test scores prior to 3G arrival; the introduction of 3G is not preceded by differential test score trends between treated and control groups.

These effect sizes qualify as medium in size, according to the schema put forth by Kraft (2020). More concretely, Bloom et al. (2008) and Evans and Yuan (2019) find that a year of schooling typically increases test score performance by 0.3 and 0.2 standard deviations, respectively.[8] Our estimates fall between one-sixth and one-half of these estimates.

Next, we describe results using instrumental variables to estimate the effects of 3G on student test scores. Here, we use the frequency of lightning strikes and the level of 2G coverage in 2007 as instruments for 3G access. Table 5 shows instrumental variables estimates of the effect of 3G on test scores in math, and science. Column 1 of Table 5 displays OLS estimates of the effect of 3G on test scores. These results are identical to those displayed in Column 1 of Table 4, and suggest small and negative effects on student test scores.

Column 2 of Table 5 displays evidence of the first stage effect of lightning strike frequency and 2007 2G coverage on 3G coverage. In these regressions, the outcome is the share of the population

[8] Bloom et al. (2008) use nationally-representative data from the U.S. The 0.3 estimate refers to the effect of a year of schooling for 8th to 9th graders, who are typically 13 to 15 years old. Evans and Yuan (2019) use a sample of test scores from low- and middle-income countries.

with 3G access. The coefficient on the interaction term Lighting $\times$ Year measures the effect of a 1 standard deviation increase in lightning strike frequency on the yearly growth of 3G access. The estimated effect size suggests that a 1 standard deviation increase in lightning strike frequency decreases the annual growth rate of 3G coverage by 0.7 percentage points. Similarly, the coefficient on the interaction term 2G $\times$ Year indicates that areas with full 2G coverage, relative to those with no 2G coverage, expanded their 3G coverage by 1 percentage point more per year.

Column 3 of Table 5 displays reduced form effects of lightning frequency and 2G coverage on test scores. Across all subjects, areas with more frequent lightning strikes exhibit higher rates of test score growth. The magnitudes of these effects are small: 0.001 to 0.003 student standard deviations. Still, relative to the first stage effects in Column 2, these suggest very large effects of 3G on student achievement. Areas with 2G coverage display the opposite pattern; higher 2G coverage is associated with lower test score growth in math and reading.

Finally, Column 4 of Table 5 shows two-stage least squares estimates of the effect of 3G access on test scores. These estimates are somewhat noisy relative to OLS estimates in Table 4; 95% confidence intervals include 0 for all subjects. Still, point estimates are all negative and fall between 0.15 and 0.3 standard deviations. Appendix Tables C.2 and C.3 display results that repeat this analysis using only the lightning and 2G instruments, respectively, with qualitatively similar results.

4.2.2 Heterogeneity

Next, we explore treatment effect heterogeneity across different subsets of students. To do so, we fully interact our OLS models with student, family, or other characteristics. Consistent with Feigenberg et al. (2023), this approach allows for the effect of 3G, as well as the effect of control variables and fixed effects, to vary across these subgroups. We explore three dimensions of heterogeneity: gender, parental education, and level of economic development.

Our results are summarized in Figure 4. Across all panels in Figure 4, we display the coefficient on $3G_{cut}$, our local, dynamic measure of 3G coverage, alongside the coefficient on the interaction term between our demographic characteristics and $3G_{cut}$. The prior coefficient represents the effect of $3G$ on the non-identified group (e.g. when the value of the demographic characteristic is equal to zero) and the latter coefficient represents the *differential* effect of 3G on the identified demographic group. All regressions in Figure 4 include country-by-year fixed effects and our baseline set of covariates; this is the same specification in Column 2 of Tables 3 and 4. Appendix Table C.5 displays the estimates across all combinations of control variables.

In Panel A of Figure 4 we test for differential effects by gender. On the whole, we find some suggestive evidence for differential effects by gender. Coefficients on interaction terms fall between -0.03 and -0.05, but are not statistically significant. While noisy, these results suggest that test scores of female students may exhibit more negative responses to 3G availability than their male counterparts.

In Panel B of Figure 4 we assess whether students whose parents have higher levels of education exhibit different test score responses in response to 3G coverage. As above, these results are noisy but suggest that students who have at least one parent with a tertiary education exhibit smaller test score declines in response to 3G coverage. In other words, test scores for students coming from less educated families are more negatively affected by 3G. These effects raise the possibility that more highly educated families may be better equipped to shield their children from the negative effects of technology.

Panel C of Figure 4 tests for heterogeneous effects of 3G with respect to whether the country is a high-income country. Specifically, we test whether students in high-income countries exhibit different responses to 3G than other students. Our set of high-income countries includes countries classified as high-income by the World Bank in 2000: 33 of the 82 countries in our sample are in this group. The results suggest that the negative effects of 3G on test scores are concentrated among non-high-income countries; the interaction terms on our high-income indicator are roughly equal and opposite-signed as our main coefficients. This could be driven by several factors. For example, this may capture the differences in whether teachers could adapt quickly and utilize technology productively in the education system.[9] Another reason could be that students and/or parents in non-high-income countries may differ in computer literacy or training to be able to navigate the internet to locate helpful online resources. Alternatively, this could also simply reflect better parental awareness of the potential downsides of internet connectivity and stronger supervision of technology use at home in high-income countries.

[9]For instance, in the UK, MyMaths, an online platform for students to practice math problems and commonly used in classrooms, was launched in 1999.

4.2.3 Potential Mechanisms

In theory, our test score results may be affected by either (a) direct exposure to and use of 3G technology (e.g. additional time spent browsing the internet) or (b) broader environmental changes caused by 3G coverage (e.g. changes in political outcomes (Melnikov, 2021; Guriev et al., 2021) or labor markets (Chiplunkar and Goldberg, 2022)) that, in turn, affect students. While we cannot distinguish between these two effects directly, variation in student technology use and test scores allows us to answer a related question: do groups of students who exhibit relatively larger test score declines exhibit relatively larger increases in technology use? As noted earlier, we find suggestive evidence that test score declines are largest among female students, among students whose parents have less education, and among students in non-high-income countries. In Appendix Table C.4, we show that these three groups also exhibit the largest increases in daily internet browsing. While not definitive, these results suggest that direct exposure to technology, rather than broader 3G-induced changes in students' environment, may explain our results.

Next, we explore potential mechanisms behind these effects by studying how 3G coverage affected student attendance, feelings of social connectedness, and mental well-being among students in our sample. The availability of these measures is somewhat limited—Appendix Figures C.2 to C.6 display their availability across countries and PISA survey rounds—so these relationships should be interpreted cautiously.

Table 6 tests whether 3G coverage is associated with changes in measures of social connectedness and mental health. All three measures are standardized such that they have a mean of zero and a standard deviation of one. Across all three measures, which relate to friendship, belonging, and self-efficacy, the effects are generally negative but vary in magnitude and statistical significance across specifications. In specifications that control for country-by-year fixed effects in Columns 2 and 4, effects on all three indices are similar in magnitude: 0.03 to 0.09 standard deviations. As a point of reference, Braghieri et al. (2022) estimate that the arrival of Facebook on college campuses reduced a similar measure of mental health by 0.085 standard deviations. These results suggest that one mechanism driving the decline in test scores could be worsened feelings of social connectivity and mental well-being. Elsewhere, Fletcher (2010) document large effects of depressive symptoms on educational attainment, even after controlling for sibling fixed effects.

Another potential mechanism through which 3G could lower student learning is through lower engagement in with school work. The arrival of mobile internet potentially changes the opportunity cost of studying, which may lead students to reduce their homework time in response to the arrival of 3G coverage. Table 7 tests whether changes in 3G coverage are associated with changes in time spent doing homework or frequency of school absences. The results in Panel A suggest that 3G coverage is associated with increases in homework time of roughly 0.5 to 1 hour per week. This result is surprising, given that it runs contrary to the effects on test scores. However, we do see that students are also more likely to have skipped school days so part of the increase in homework hours could simply reflect students trying to compensate for missed days. Panel B shows the estimated effects of 3G coverage on student absenteeism, which are consistently positive but vary substantially across specifications.

Finally, we explore the relationship between these candidate mechanisms and student demographic characteristics. Figures 5 and 6 summarize the results of heterogeneity analyses with respect to feelings of social connectedness, mental health outcomes and academic behavioral outcomes, respectively. We highlight two notable results that warrant further investigation.

First, our results in Panel A of Figure 5 suggest that the negative effects of 3G on adolescent mental health are concentrated among girls rather than boys. This is also consistent with results in Golin (2022), who finds that "broadband Internet leads to worse mental health for women [...] but not for men." Second, while our main results found limited effects on students' self-efficacy, Panel B of 5 suggests that 3G coverage may lower self-efficacy among students whose parents have less education, with limited effects on students from higher education backgrounds. Appendix Tables C.6 and C.7 display corresponding estimates across all combinations of control variables, with similar results.

5 Conclusion

The proliferation of information technology has rapidly changed the lives of adolescents worldwide. Do these changes improve or hamper learning? Public discourse surrounding this question spans a large spectrum. Proponents argue that information technology can expand access to information and educational resources, potentially enhancing student learning. Conversely, there are concerns about the adverse effects of these technologies on sleep, mental health, and various aspects of students' lives, which could impede their learning and skill development. The evidence presented here suggests that these concerns about the impact of internet use on student achievement may be valid; expansion of internet access via 3G coverage is associated with reductions in student achievement.

Our results warrant many avenues for future research; we highlight two in particular. First, given that technology plays a complex and changing role in adolescents' lives, future research can help to understand potential mechanisms and circumstances that allow technology to augment, rather than hamper student learning. Second, we note that the set of skills measured in PISA exams is limited to math, science, and reading, and our set of behavioral and mental health measures is quite limited. Future research that quantifies the myriad of skills and factors that contribute to students' overall well-being and success in the modern world will be extremely valuable.

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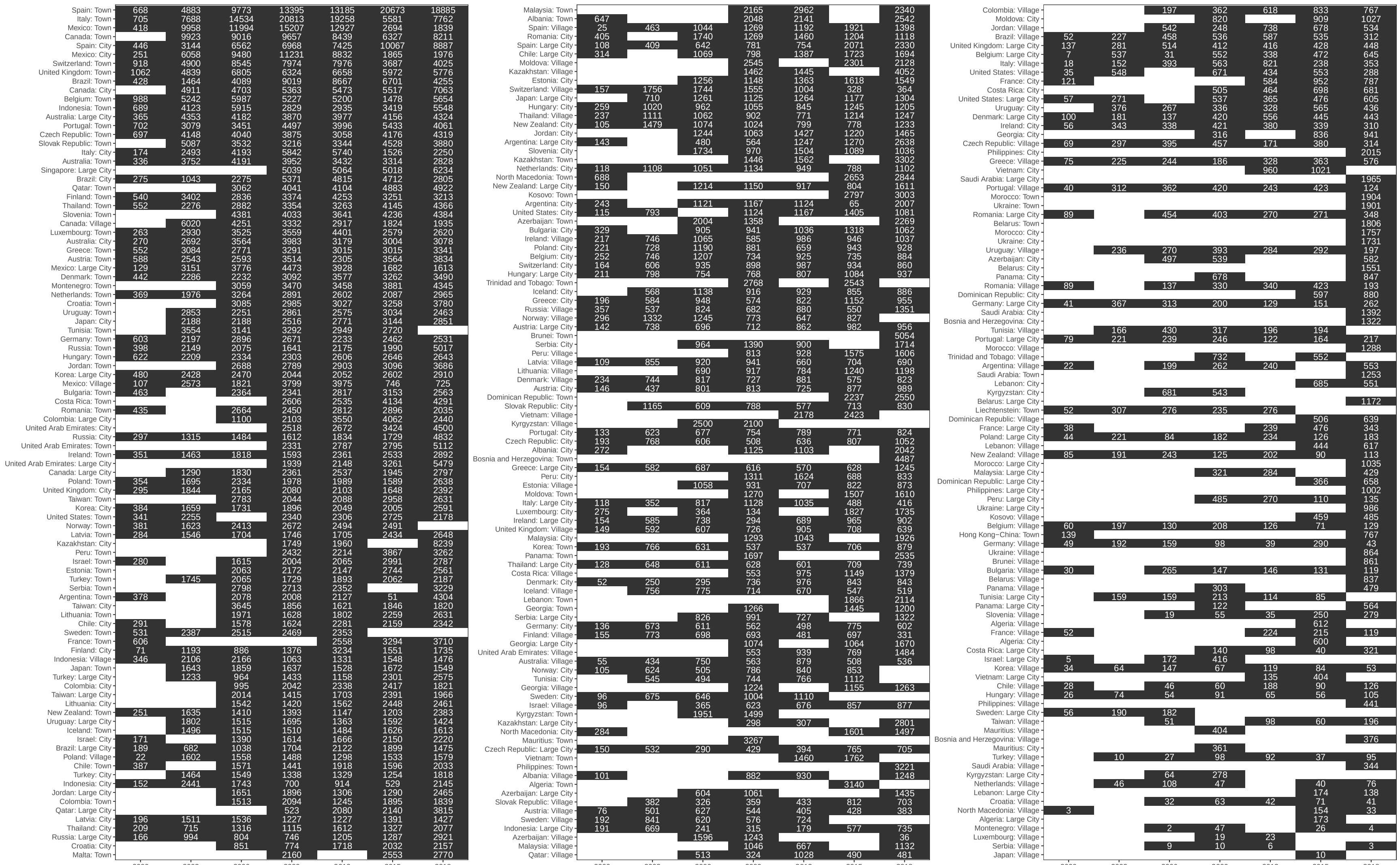

Figure 1: Data Coverage by Country and Year

Note: Figure displays the number of observations in each country-by-urbanicity cell.

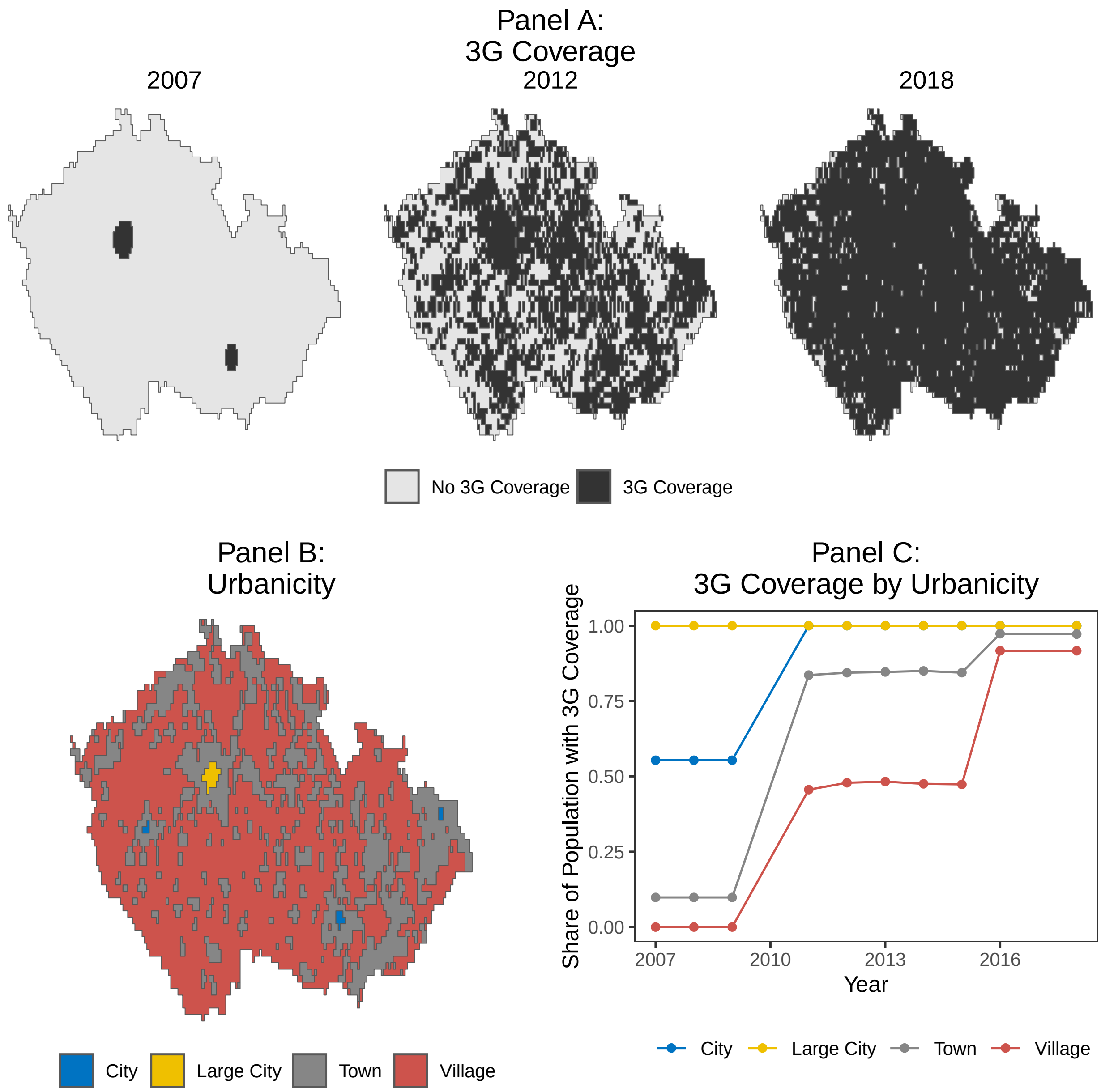

Figure 2: 3G Expansion in the Czech Republic

Note: Figure summarizes the calculation for 3G expansion in the Czech Republic. Panel A displays 3G coverage in 2007, 2012, and 2018. Panel B displays geographical variation in urbanicity, as described in the text. Panel C displays variation in 3G coverage over time by urbanicity.

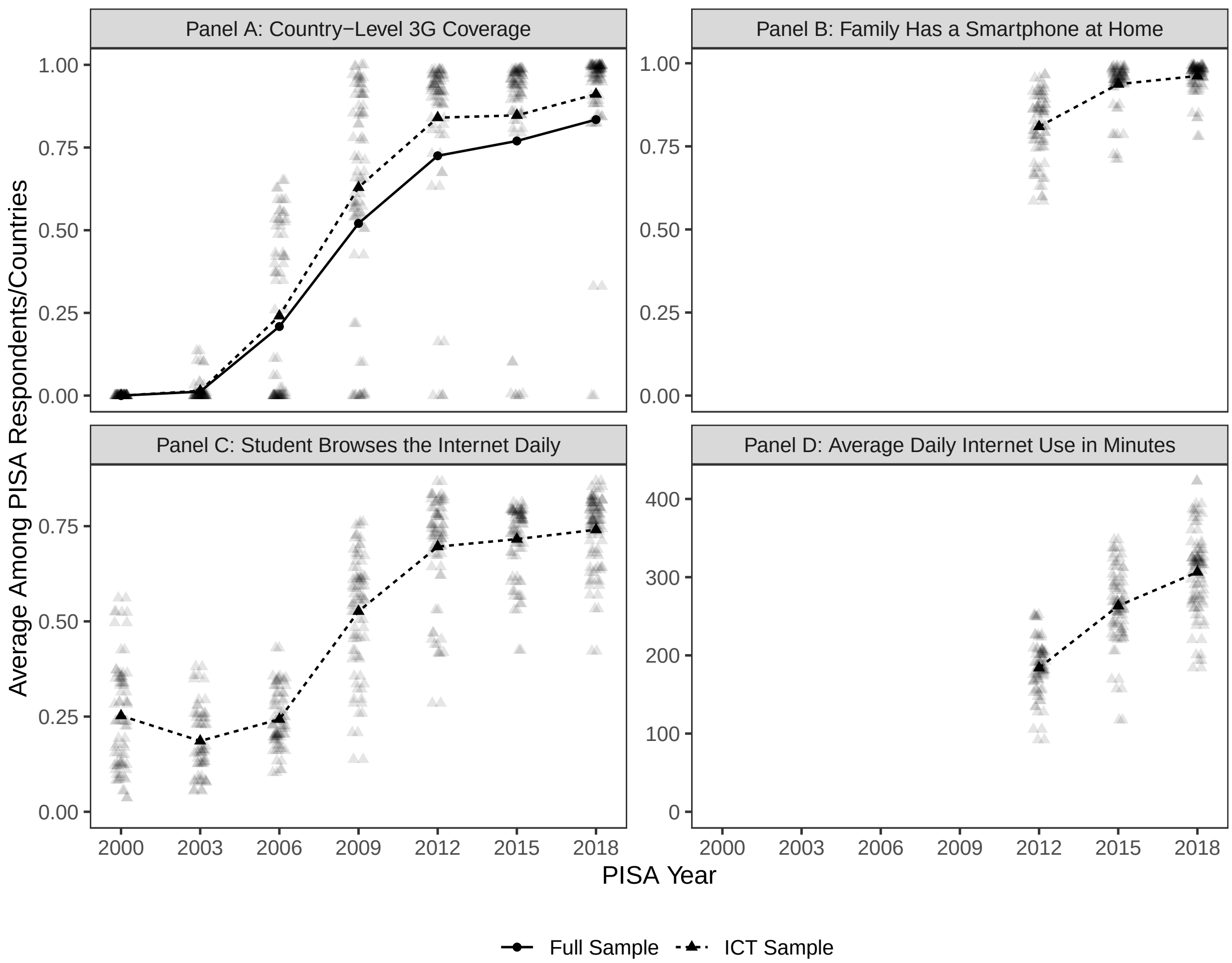

Figure 3: Trends in Internet Access and Use in PISA Countries

Note: Figure displays trends in internet access and use in PISA countries. Points reflect country-level averages for observations in the ICT sample. Each country-level average is weighted by PISA sampling weights. Full lines reflect the average country-level values each year in the sample, and dashed lines reflect average country-level values in the ICT sample.

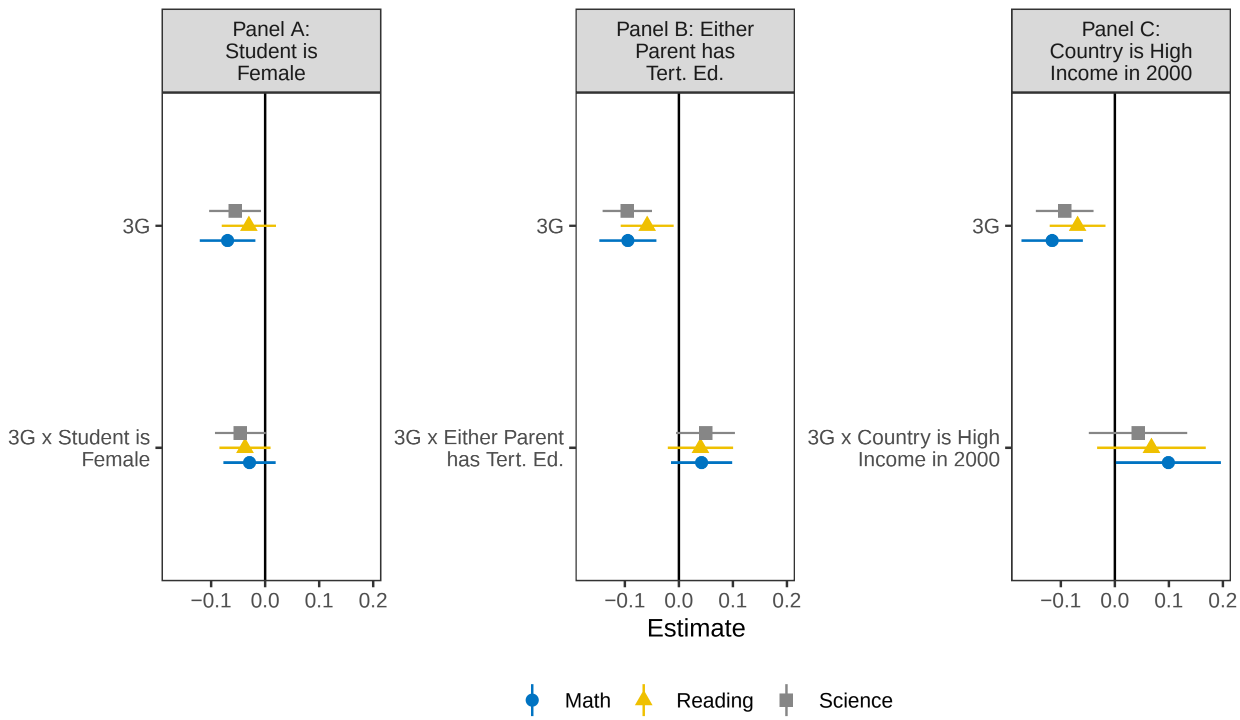

Figure 4: Heterogeneous Effects of 3G on PISA Test Scores

Note: Figure displays OLS results estimating the heterogeneous effect of 3G coverage on test scores. Dependent variables are scaled student test scores in math, reading, and science. The displayed coefficients show the effect of 3G as well as the interaction effect between 3G and the demographic characteristics labeled in each panel. All regressions include country fixed effects, year fixed effects, country-by-year fixed effects, and baseline controls (student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend). Error bars indicate 95% confidence intervals. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. See Appendix Table C.5 for corresponding coefficient estimates.

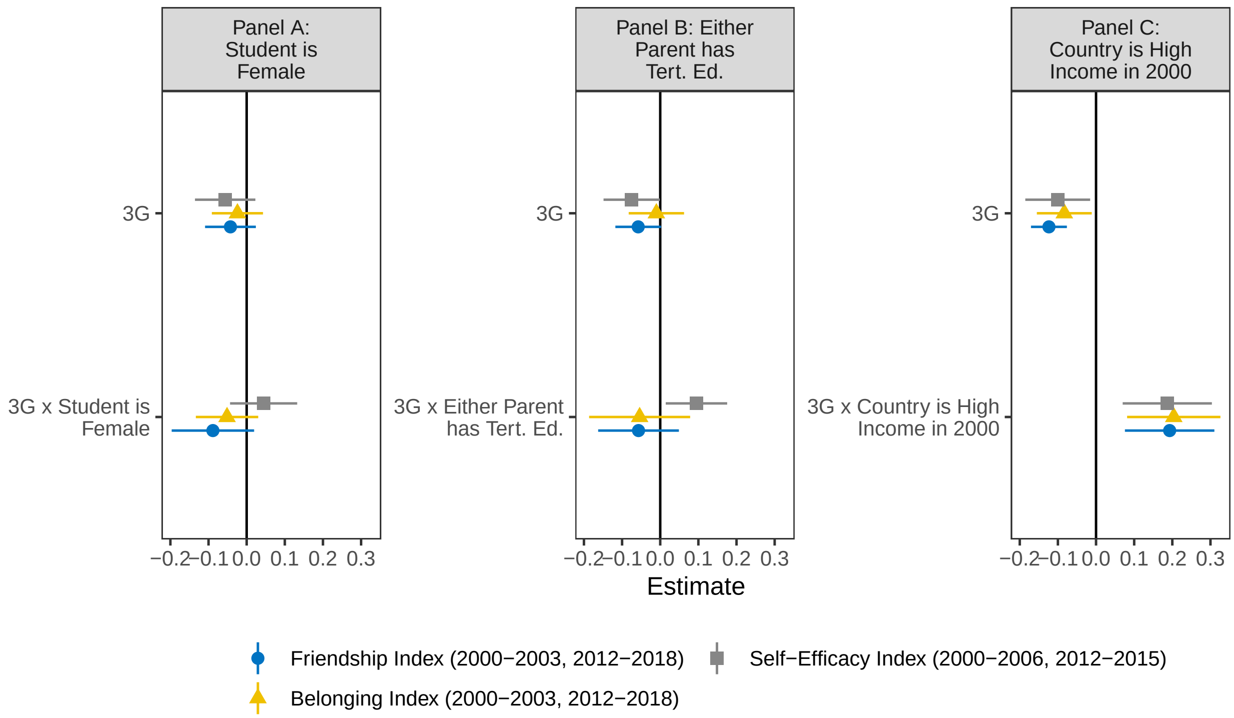

Figure 5: Heterogeneous Effects of 3G on Social Well-Being and Mental Health

Note: Figure displays OLS results estimating the heterogeneous effect of 3G coverage on social well-being and mental health. Dependent variables are indices with a mean of 0 and a standard deviation of 1. The displayed coefficients show the effect of 3G as well as the interaction effect between 3G and the demographic characteristics labeled in each panel. All regressions include country fixed effects, year fixed effects, country-by-year fixed effects, and baseline controls (student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend). Error bars indicate 95% confidence intervals. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. See Appendix Table C.6 for corresponding coefficient estimates. These variables are not available for all countries in all years; see Appendix Figures C.4, C.5, and C.6.

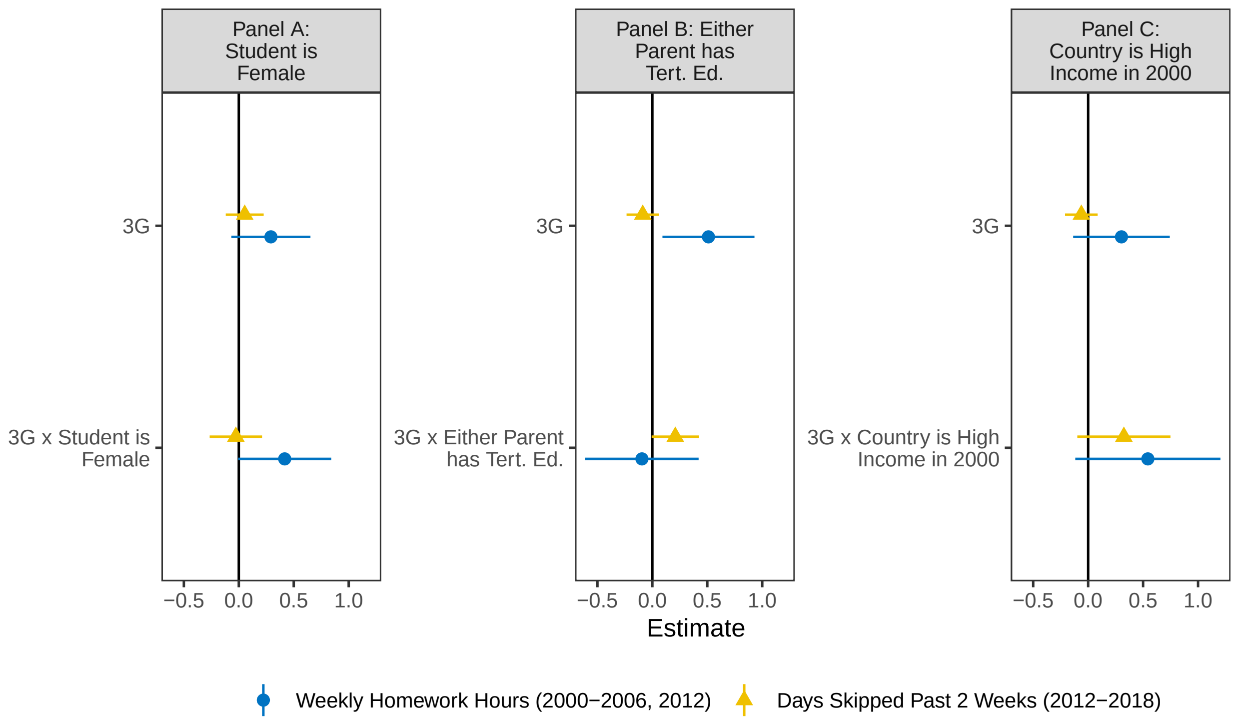

Figure 6: Heterogeneous Effects of 3G on Homework and Absenteeism

Note: Figure displays OLS results estimating the heterogeneous effect of 3G coverage on homework and absenteeism. The displayed coefficients show the effect of 3G as well as the interaction effect between 3G and the demographic characteristics labeled in each panel. All regressions include country fixed effects, year fixed effects, country-by-year fixed effects, and baseline controls (student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend). Error bars indicate 95% confidence intervals. Observations are weighted by $w_{ic}/\sum_{i\in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i\in c} w_{ic}$ denotes the sum of sampling weights in country c. See Appendix Table C.7 for corresponding coefficient estimates. These variables are not available for all countries in all years; see Appendix Figures C.2 and C.3.

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.
Panel A: Full Sample			
Male	2,286,455	0.493	0.500
Age	2,286,455	15.785	0.292
Is Immigrant	2,286,455	0.049	0.216
Father's Years of Education	2,286,455	13.068	4.254
Mother's Years of Education	2,286,455	13.048	4.314
School is Private, Independent	2,286,455	0.075	0.264
School is Private, Non-Independent	2,286,455	0.085	0.279
Weekly Homework Hours (2000-2006, 2012)	792,899	6.455	5.386
Days Skipped Past 2 Weeks (2012-2018)	1,124,738	0.828	1.470
Friendship Index (2000-2003, 2012-2018)	1,318,338	0.001	1.000
Belonging Index (2000-2003, 2012-2018)	1,325,812	−0.016	0.985
Self-Efficacy Index (2000-2006, 2012-2015)	1,194,178	0.007	1.056
Math Score	2,286,455	−0.316	0.988
Reading Score	2,286,455	−0.324	1.003
Science Score	2,286,455	−0.272	0.983
Share of Population with 3G Coverage	2,286,455	0.578	0.423
Panel B: ICT Sample			
Male	1,435,055	0.491	0.500
Age	1,435,055	15.784	0.292
Is Immigrant	1,435,055	0.045	0.207
Father's Years of Education	1,435,055	13.314	3.958
Mother's Years of Education	1,435,055	13.375	3.962
School is Private, Independent	1,435,055	0.058	0.234
School is Private, Non-Independent	1,435,055	0.104	0.305
Weekly Homework Hours (2000-2006, 2012)	556,315	6.451	5.353
Days Skipped Past 2 Weeks (2012-2018)	714,440	0.757	1.397
Friendship Index (2000-2003, 2012-2018)	846,640	−0.012	0.992
Belonging Index (2000-2003, 2012-2018)	851,003	0.011	1.003
Self-Efficacy Index (2000-2006, 2012-2015)	801,624	0.029	1.046
Math Score	1,435,055	−0.098	0.937
Reading Score	1,435,055	−0.113	0.941
Science Score	1,435,055	−0.064	0.935
Share of Population with 3G Coverage	1,435,055	0.619	0.419
Browses the Internet Daily	1,435,055	0.532	0.499
Has a Smartphone at Home (2012-2018)	757,469	0.901	0.299
Average Daily Internet Use in Minutes (2012-2018)	757,469	252.083	192.135

Note: Table displays summary statistics for PISA data. Panel A displays summary statistics for the full PISA sample, which includes all student observations for which data is available for main testing and control variables. Panel B displays summary statistics for the ICT sample, which additionally requires that observations have non-missing responses to the main ICT variables.

Table 2: Associations Between Digital Technology Use and PISA Test Scores

	(1)	(2)	(3)	(4)
Panel A: Math				
Average Daily Internet Use in Hours	-0.032***			-0.039***
	(0.002)			(0.002)
Has a Smartphone at Home		0.025*		0.036**
		(0.012)		(0.011)
Browses Internet Daily			0.134***	0.192***
			(0.014)	(0.013)
Num.Obs.	705619	705619	705619	705619
R2	0.326	0.315	0.319	0.334
Panel B: Reading				
Average Daily Internet Use in Hours	-0.028***			-0.037***
	(0.002)			(0.002)
Has a Smartphone at Home		0.045***		0.043***
		(0.013)		(0.011)
Browses Internet Daily			0.212***	0.266***
			(0.015)	(0.014)
Num.Obs.	705619	705619	705619	705619
R2	0.274	0.267	0.276	0.289
Panel C: Science				
Average Daily Internet Use in Hours	-0.031***			-0.039***
	(0.002)			(0.002)
Has a Smartphone at Home		0.018		0.022*
		(0.012)		(0.011)
Browses Internet Daily			0.177***	0.235***
			(0.013)	(0.013)
Num.Obs.	705619	705619	705619	705619
R2	0.287	0.277	0.283	0.298
Country-by-Urbanicity FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓

Note: Table displays OLS results estimating the association between technology use and test scores. Data includes all observations in the ICT sample from years 2012, 2015, and 2018. Dependent variables are indicated in panel labels. Baseline controls include student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3: OLS Estimates: Effect of 3G on Technology Access and Use

	(1)	(2)	(3)	(4)
Panel A: Browses the Internet Daily				
3G	0.043+	0.068***	0.039	0.068***
	(0.024)	(0.020)	(0.024)	(0.019)
Num.Obs.	1435055	1435055	1435055	1435055
R2	0.250	0.271	0.257	0.277
Panel B: Has a Smartphone at Home (2012-2018)				
3G	0.053	0.033	0.054	0.041
	(0.035)	(0.025)	(0.034)	(0.026)
Num.Obs.	757469	757469	757469	757469
R2	0.114	0.124	0.123	0.132
Panel C: Has a Smartphone at Home (2012-2018; 2000, 2003 Set to 0)				
3G	0.102**	0.120**	0.101**	0.122**
	(0.034)	(0.044)	(0.035)	(0.045)
Num.Obs.	959418	959418	959418	959418
R2	0.799	0.803	0.801	0.805
Panel D: Average Daily Internet Use in Minutes (2012-2018)				
3G	39.515***	41.018*	36.329***	34.934*
	(9.370)	(15.949)	(8.979)	(15.244)
Num.Obs.	757469	757469	757469	757469
R2	0.125	0.131	0.141	0.147
Country-by-Urbanicity FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓
Country-by-Year FES		✓		✓
Controls Interacted with Country-by-Urbanicity			✓	✓

Note: Table displays OLS results estimating the effect of 3G coverage on technology access and use. Dependent variables are indicated in panel labels. Baseline controls include student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4: OLS Estimates: Effect of 3G on PISA Test Scores

	(1)	(2)	(3)	(4)
Panel A: Math				
3G	-0.031	-0.084***	-0.033	-0.080***
	(0.029)	(0.024)	(0.028)	(0.022)
Num.Obs.	2286455	2286455	2286455	2286455
R2	0.373	0.383	0.398	0.408
Panel B: Reading				
3G	-0.056+	-0.047*	-0.058+	-0.048*
	(0.032)	(0.023)	(0.030)	(0.021)
Num.Obs.	2286455	2286455	2286455	2286455
R2	0.344	0.356	0.370	0.381
Panel C: Science				
3G	-0.019	-0.079***	-0.021	-0.078***
	(0.024)	(0.022)	(0.023)	(0.021)
Num.Obs.	2286455	2286455	2286455	2286455
R2	0.331	0.340	0.358	0.367
Country-by-Urbanicity FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓
Country-by-Year FES		✓		✓
Controls Interacted with Country-by-Urbanicity			✓	✓

Note: Table displays OLS results estimating the effect of 3G coverage on test scores. Dependent variables are scaled student test scores in math (Panel A), reading (Panel B), and science (Panel C). Baseline controls include student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5: IV Estimates: Effect of 3G on PISA Test Scores

	(1)	(2)	(3)	(4)
	OLS	FS	RF	IV
Dep. Var	Score	3G	Score	Score
Panel A: Math				
3G	-0.031			
	(0.029)			
Lightning × Year		-0.007***	0.003+	
		(0.002)	(0.001)	
2G × Year		0.008	-0.001	
		(0.005)	(0.005)	
$\widehat{3G}$				-0.341+
				(0.193)
Num.Obs.	2286455	2286455	2286455	2286455
R2	0.373	0.864	0.373	0.370
Panel B: Reading				
3G	-0.056+			
	(0.032)			
Lightning × Year		-0.007***	0.001	
		(0.002)	(0.001)	
2G × Year		0.008	-0.005	
		(0.005)	(0.005)	
$\widehat{3G}$				-0.188
				(0.172)
Num.Obs.	2286455	2286455	2286455	2286455
R2	0.344	0.864	0.344	0.344
Panel C: Science				
3G	-0.019			
	(0.024)			
Lightning × Year		-0.007***	0.002*	
		(0.002)	(0.001)	
2G × Year		0.008	0.004	
		(0.005)	(0.004)	
$\widehat{3G}$				-0.246
				(0.151)
Num.Obs.	2286455	2286455	2286455	2286455
R2	0.331	0.864	0.331	0.330
Country-by-Urbanicity FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓

Note: Table displays instrumental variables results estimating the effect of 3G coverage on test scores. Column 1 displays OLS results. Column 2 displays the first stage results. Column 3 displays reduced form results. Column 4 displays two-stage least squares results. Dependent variables in Columns 1, 3, and 4 are scaled student test scores in math (Panel A), reading (Panel B), and science (Panel C). The dependent variable in Column 2 is 3G coverage. Baseline controls include student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6: OLS Estimates: Effect of 3G on Social Well-Being and Mental Health

	(1)	(2)	(3)	(4)
Panel A: Friendship Index (2000-2003, 2012-2018)				
3G	-0.010	-0.089***	-0.004	-0.089***
	(0.042)	(0.022)	(0.041)	(0.023)
Num.Obs.	1318338	1318338	1318338	1318338
R2	0.033	0.041	0.039	0.047
Panel B: Belonging Index (2000-2003, 2012-2018)				
3G	-0.049	-0.047	-0.046	-0.058+
	(0.057)	(0.032)	(0.053)	(0.033)
Num.Obs.	1325812	1325812	1325812	1325812
R2	0.039	0.054	0.048	0.061
Panel C: Self-Efficacy Index (2000-2006, 2012-2015)				
3G	0.017	-0.037	0.013	-0.032
	(0.055)	(0.032)	(0.055)	(0.033)
Num.Obs.	1194178	1194178	1194178	1194178
R2	0.053	0.071	0.065	0.082
Country-by-Urbanicity FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓
Country-by-Year FES		✓		✓
Controls Interacted with Country-by-Urbanicity			✓	✓

Note: Table displays OLS results estimating the effect of 3G coverage on social well-being and mental health. Dependent variables are indices with a mean of 0 and a standard deviation of 1. Baseline controls include student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. These variables are not available for all countries in all years; see Appendix Figures C.4, C.5, and C.6. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 7: OLS Estimates: Effect of 3G on Homework and Absenteeism

	(1)	(2)	(3)	(4)
Panel A: Weekly Homework Hours (2000-2006, 2012)				
3G	0.987***	0.513**	1.045***	0.552**
	(0.259)	(0.171)	(0.261)	(0.173)
Num.Obs.	792899	792899	792899	792899
R2	0.136	0.160	0.150	0.174
Panel B: Days Skipped Past 2 Weeks (2012-2018)				
3G	0.413***	0.041	0.421***	0.045
	(0.094)	(0.088)	(0.093)	(0.086)
Num.Obs.	1124738	1124738	1124738	1124738
R2	0.112	0.127	0.122	0.137
Country-by-Urbanicity FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓
Country-by-Year FES		✓		✓
Controls Interacted with Country-by-Urbanicity			✓	✓

Note: Table displays OLS results estimating the effect of 3G coverage on homework and absenteeism. Baseline controls include student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. These variables are not available for all countries in all years; see Appendix Figures C.2 and C.3. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

A PISA Variables Construction

In this Appendix, we describe our process of quantizing and harmonizing variables across different PISA rounds. We use the `EdSurvey` package in `R` to import and append PISA data.

A.1 Mother's and Father's Years of Education

PISA data records the 1997 ISCED code of the highest level of education for each student's mother and father. We convert ISCED categories into years of education, assuming that ISCED code 0 (pre-primary education) corresponds to 0 years, ISCED code 1 (primary education) corresponds to 6 years, ISCED code 2 (lower secondary education) corresponds to 9 years, ISCED codes 3 (upper secondary education) and 4 (post-secondary non-tertiary education) correspond to 13 years, and ISCED codes 5 (first stage of tertiary education) and 6 (second stage of tertiary education) correspond to 17 years. We use this grouping because some rounds of PISA group these ISCED codes together.

A.2 Test Scores

PISA test scores are reported as plausible values, which provide a range of scores that are consistent with the observed responses. For simplicity, we use the average of plausible values for all subjects.

A.3 Internet Browsing Frequency

Between 2000 and 2018, PISA asked students various questions about student internet use. For each year, we identify the question that comes closest to gauging the respondent's frequency of internet use. These questions are listed below, separately by year.

- **2000**: How often do you read these materials because you want to: [...] Emails and Web pages
- **2003** How often do you use: [...] the Internet to look up about people, things, or ideas?
- **2006**: How often do you use computers for the following reasons? [...] Browse the Internet for information about people, things, or ideas
- **2009**: How often do you use a computer for following activities at home? [...] Browse the Internet for fun (such as watching videos, e.g. <YouTube™>)
- **2012** How often do you use a computer for the following activities outside of school? [...] Browsing the Internet for fun (such as watching videos, e.g. <YouTube™>).
- **2015**: How often do you use digital devices for the following activities outside of school? [...] Browsing the Internet for fun (such as watching videos, e.g. <YouTube™>).
- **2018**: How often do you use digital devices for the following activities outside of school? [...] Browsing the Internet for fun (such as watching videos, e.g. <YouTube™>).

For simplicity, we measure these responses in the form of a binary indicator identifying whether the respondent uses the internet daily. In one year, 2000, the PISA questionnaire did not include “daily" as a response. In this case, we code responses of “several times a week" as equal to one.

A.4 Length of Daily Internet Use

In 2012, 2015, and 2018, PISA’s ICT questionnaire asked students the following questions:

- During a typical weekday, for how long do you use the Internet at school?
- During a typical weekday, for how long do you use the Internet outside of school?
- On a typical weekend day, for how long do you use the Internet outside of school?

For each question, students choose between the following responses:

- No time
- 1-30 minutes per day
- 31-60 minutes per day
- Between 1 and 2 hours per day
- Between 2 and 4 hours per day
- Between 4 hours and 6 hours per day
- More than 6 hours per day

We calculate the total amount of time associated with each response as the mid-point between the upper and lower bounds. For example, we assume that “Between 1 and 2 hours per day" corresponds to 90 minutes. We additionally assume that “More than 6 hours per day" corresponds to 8 hours. Finally, we calculate the average amount of time spent daily according to the equation below.

$$\begin{aligned}\text{Avg. Weekly Internet} =& \frac{5 * \text{Wkday Int. Time} + 2 * \text{Wknd Int. Time}}{7} \\ =& \frac{5}{7}(\text{Wkday School Int. Time + Wkday Non-School Int. Time}) \\ &+ \frac{2}{7}(\text{Wknd Int. Time})\end{aligned}$$

A.5 Homework Time

PISA questionnaires in 2000, 2003, 2006, 2012, and 2015 asked about weekly time spent on homework. In 2003, 2012, and 2015, questionnaires asked about total homework time in hours and allowed students to respond freely. In other years, PISA asked about total homework time separately by subject (math, reading, science, other) and gave students a set of time ranges (e.g. “Less than 1 hour per week," "1 to 3 hours per week," "More than 3 hours per week") from which to choose. In these instances, we convert these values based on the midpoint of the range (assuming more than 3 hours corresponds to 4 hours) and sum across subjects. This means that, in some years, the largest possible value for student homework time is 12 hours. For consistency, we re-code responses above 12 hours per week to be equal to 12 hours per week. Finally, we exclude data from 2015 due to extreme values: many students report spending more than 40 hours per week on homework and in some cases as much as 70 hours.

A.6 Absenteeism

In 2012, 2015, and 2018, PISA questionnaires asked students how frequently they skipped a whole day or some of a day of school over the past two weeks. Eligible responses were "None," "One or two times," "Three or four times," "Five or more times." We convert this to a numeric value by taking the midpoint of each range and assuming "Five or more times" corresponds to 5. Finally, we calculate the total days of school missed as the sum of (a) whole days skipped and (b) one-half times some days skipped.

A.7 Social and Mental Health Measures

Some rounds of PISA data include two constructed indices—a "belonging" index and a "self-efficacy" index—that summarize responses to a number of mental health-related questions. The belonging index captures student responses to statements about feeling like an outsider, making friends easily at school, feeling a sense of belonging, feeling awkward and out of place, and how well-liked the student feels by other students. The self-efficacy index is available periodically for different subjects over time, with slightly different definitions. As an example, in 2012, the OEDC measured self-efficacy in math as "the extent to which students believe in their own ability to solve specific mathematics tasks." We harmonize this index over time by taking overall self-efficacy in 2000, math self-efficacy in 2003 and 2012, and science self-efficacy in 2006 and 2015. Finally, many rounds of PISA asked students the degree to which they agreed with the statement "I make friends easily at school." Eligible responses were "strongly agree," "agree," "disagree," and "strongly disagree." We transform these responses into integers 0 through 3 and standardize this value such that it is mean 0 and standard deviation 1.

B Two-Stage Difference in Differences Estimates

As described briefly in the main text, we use the two-stage difference in differences estimator from Gardner et al. (2023) to assess whether our main results are driven by potential bias from two-way fixed effects estimation. The two-stage difference-in-difference estimator uses only untreated observations in the first stage. Because our measure of treatment—3G coverage—is continuous, the set of observations that are deemed untreated depends on the threshold used to distinguish treated versus untreated observations. As such, we estimate separate models with three thresholds of treatment: the first considers observations untreated only if the level of 3G coverage is exactly 0, whereas the second and third consider observations untreated if the level of 3G coverage is less than 25% or 50%, respectively. In the second stage, we use our continuous 3G measure to estimate treatment effects after removing the group and period fixed effects estimated in the first stage using only untreated observations.

In these settings, it is also common to present event studies to show estimated treatment effects as a function of time since treatment. We use two-stage differences-in-differences to estimate event studies that estimate treatment effects for each period before and after treatment. We estimate these effects for each three-year period before and after treatment (e.g. 0 to 2 years, 3 to 5 years, etc.). We estimate these effects relative to the latest pre-treatment period: 1 to 3 years before treatment. To ensure that all county-by-urbanicity pairs have such a reference period, we estimate these models using only country-by-urbanicity pairs that appear in all 6 PISA rounds between 2003 and 2018. We refer to this sample as the "balanced sample." For completeness, I include estimates using this "balanced sample" in the difference-in-differences tables below.

Appendix Table B.1 summarizes our results with respect to technology access and use. Only two of the four variables included in Table 3 have sufficient availability over time to allow us to estimate the two-stage difference-in-differences estimates. In Panel A, we present estimates of effects on the likelihood of browsing the internet daily. Columns 1 through 4 use the full ICT sample, identical to the sample used in our main estimates in Table 3. Columns 5 through 8 use the balanced ICT sample, which includes only country-by-urbanicity pairs that have ICT data for all 6 PISA rounds. Columns 1 and 5 contain OLS estimates; all other columns contain the two-stage difference-in-difference estimates, varying the threshold of 3G coverage used to identify treated versus untreated units.

Estimates in Columns 1 to 4 of Panel A of Table B.1 show that the arrival of 3G coverage is associated with an increase in student internet browsing. Here, two-stage difference-in-differences estimates are uniformly larger in magnitude than OLS estimates. Estimates in Columns 5 to 8 of Panel A of Table B.1 are still positive, but estimates are smaller and less precise. This may be, in part, due to a large reduction in the set of countries included in the balanced ICT sample: only 20 unique countries appear in the sample, compared to 66 countries in the full ICT sample. Results in Panel B are consistent across samples and methods and suggest that the arrival of 3G coverage is associated with an increase in smartphone ownership of roughly 10 percentage points.

Appendix Table B.2 summarizes our results with respect to test scores. Consistent with the estimates provided in the body of the paper, our estimates suggest that 3G coverage is associated with lower scores on PISA exams, using both the full sample (shown in Columns 1 through 4) as well as the balanced sample (shown in Columns 5 through 8). Generally, estimates using two-stage differences-in-differences are slightly larger in magnitude than estimates using OLS.

Figure B.1 shows our event study results with respect to 3G coverage (in Panel A) and test scores (in Panel B). In each Panel, we present estimates using the three 3G treatment thresholds described above. Because the PISA exam takes place every three years, we use 3-year groups In Panel A, we confirm that our calculation of 3G entry years is correct; upon 3G entry, 3G coverage exhibits a large and sustained increase. The magnitude of this increase is the largest for our estimates that use the lowest treatment threshold. This is expected; using a lower threshold for treatment implies that control units have lower levels of 3G coverage, so comparisons between treated and control units will produce larger estimates. In Panel B, we show dynamic treatment effects on PISA scores in math, reading, and science. Across all three subjects, the arrival of 3G is associated with a decline in test scores, which grows over time. Importantly, these changes are not preceded by systematic differences in the trends between treated and untreated groups; event study estimates for periods prior to 3G arrival are generally small and insignificant.

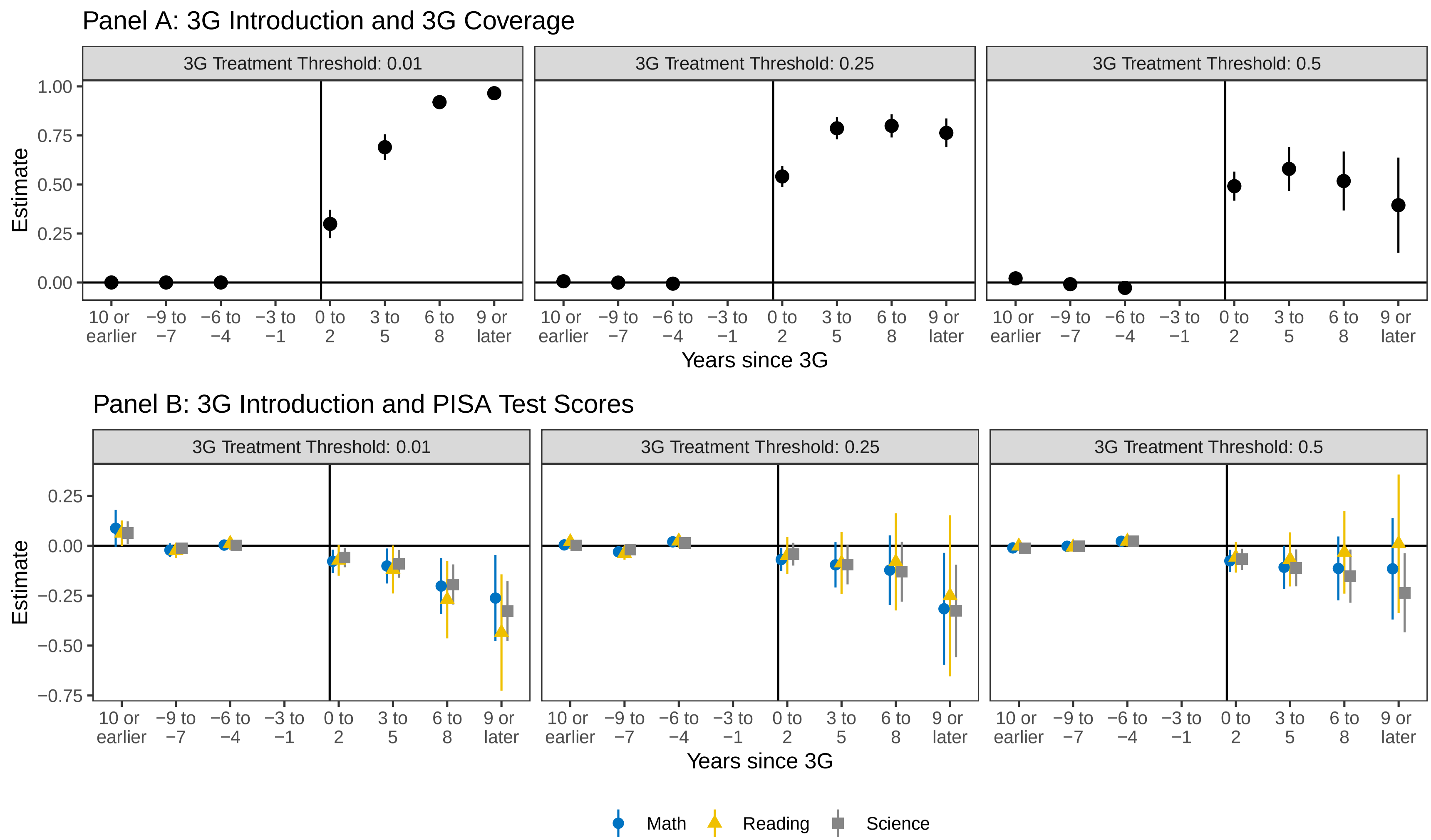

Figure B.1: Effect of 3G Entry on PISA Test Scores: Two-Stage Difference in Differences

Note: Figure displays event study estimates using two-stage difference-in-differences and the balanced sample. Dependent variables are indicated in panel labels. Baseline controls include student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001..

Table B.1: OLS and 2SDiD Estimates: Effect of 3G on Technology Access and Use

	Full ICT Sample				Balanced ICT Sample			
Method:	OLS	2SDiD			OLS	2SDiD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Browses the Internet Daily								
3G	0.043+	0.283***	0.102**	0.099**	-0.045	0.026	0.048	0.043
	(0.024)	(0.030)	(0.033)	(0.038)	(0.030)	(0.049)	(0.045)	(0.037)
Num.Obs.	1435055	1261782	1326936	1337909	695153	464304	483095	581869
R2	0.250	0.075	0.011	0.011	0.263	0.001	0.002	0.002
Panel B: Has a Smartphone at Home (2012-2018; 2000, 2003 Set to 0)								
3G	0.102**	0.448***	0.114***	0.140**	0.131***	0.154***	0.163***	0.123***
	(0.034)	(0.023)	(0.031)	(0.045)	(0.031)	(0.027)	(0.042)	(0.034)
Num.Obs.	959418	794660	841547	841965	467249	236565	246273	348076
R2	0.799	0.251	0.059	0.085	0.833	0.081	0.090	0.067
3G Treatment Threshold	-	0.01	0.25	0.5	-	0.01	0.25	0.5
Country-by-Urbanicity FEs	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓

Note: Table displays OLS and two-stage difference-in-differences results estimating the effect of 3G entry on 3G coverage (in Panel A) and test scores (in Panel B). All regressions include country-by-urbanicity fixed effects, year fixed effects, and baseline controls (student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend). Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.2: OLS and 2SDiD Estimates: Effect of 3G on PISA Test Scores

	Full Sample				Balanced Sample			
Method:	OLS	2SDiD			OLS	2SDiD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Math								
3G	-0.031	-0.209***	-0.098**	-0.090**	-0.085*	-0.194**	-0.196*	-0.112
	(0.029)	(0.048)	(0.038)	(0.034)	(0.035)	(0.069)	(0.098)	(0.081)
Num.Obs.	2286455	1948676	2081878	2128519	1458474	973571	1458474	1458474
R2	0.373	0.012	0.003	0.003	0.294	0.008	0.012	0.004
Panel B: Reading								
3G	-0.056+	-0.322***	-0.165***	-0.139**	-0.067	-0.250*	-0.153	-0.038
	(0.032)	(0.055)	(0.047)	(0.045)	(0.042)	(0.101)	(0.140)	(0.108)
Num.Obs.	2286455	1948676	2081878	2128519	1458474	973571	1458474	1458474
R2	0.344	0.025	0.008	0.006	0.263	0.014	0.007	0.000
Panel C: Science								
3G	-0.019	-0.318***	-0.179***	-0.161***	-0.023	-0.186***	-0.197*	-0.159*
	(0.024)	(0.049)	(0.043)	(0.042)	(0.031)	(0.052)	(0.083)	(0.066)
Num.Obs.	2286455	1948676	2081878	2128519	1458474	973571	1458474	1458474
R2	0.331	0.025	0.010	0.008	0.254	0.008	0.012	0.008
3G Treatment Threshold	-	0.01	0.25	0.5	-	0.01	0.25	0.5
Country-by-Urbanicity FEs	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓

Note: Table displays OLS and two-stage difference-in-differences results estimating the effect of 3G coverage on test scores. Dependent variables are indicated in panel labels. Baseline controls include student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

C Additional Figures and Tables

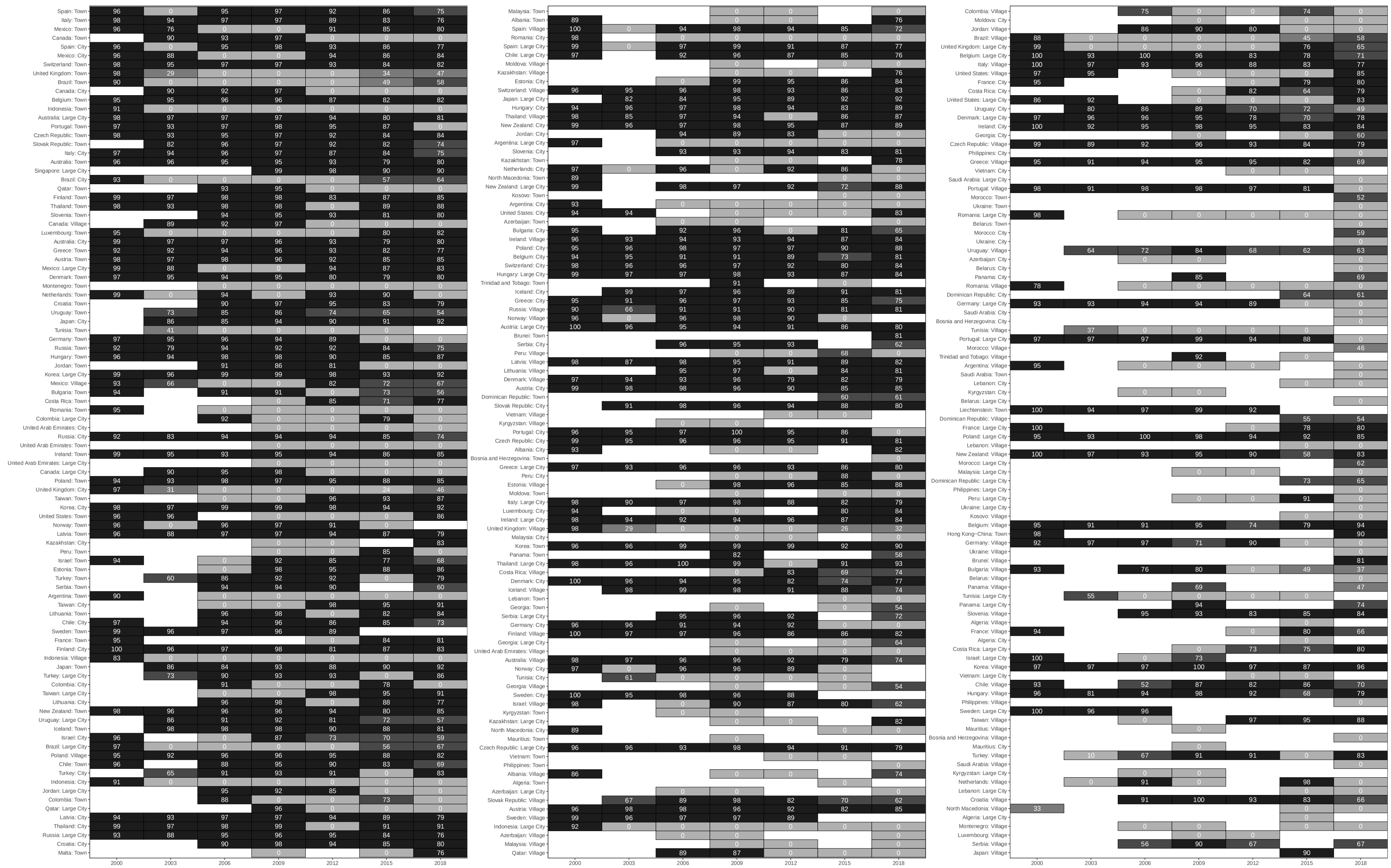

Figure C.1: ICT Sample: Data Availability by Country and Year

Note: Figure displays the share (in percentages ranging from 0 to 100) of full sample observations that appear in the ICT sample, separately for each country-by-urbanicity cell.

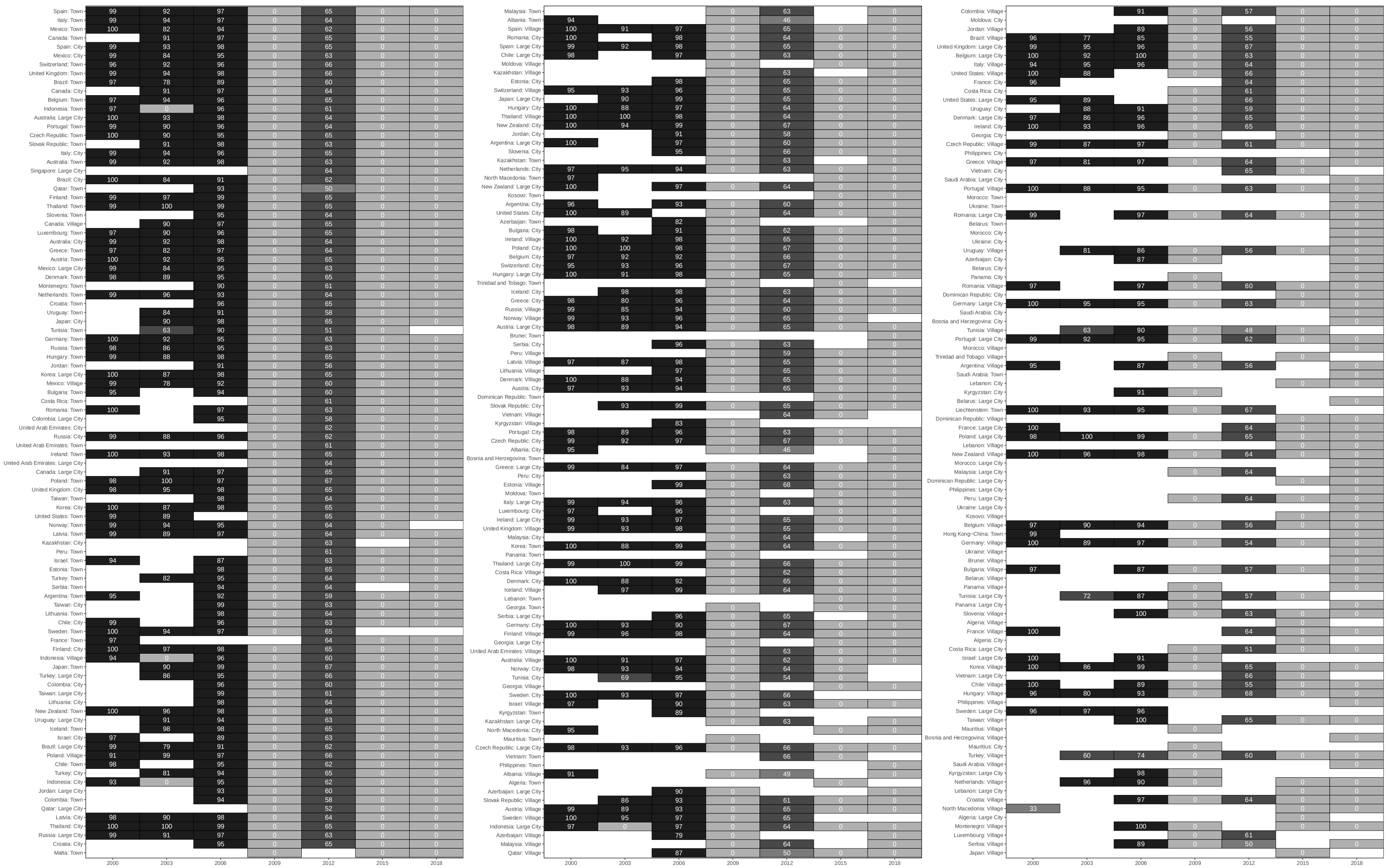

Figure C.2: Weekly Homework Hours: Data Availability by Country and Year

Note: Figure displays the share (in percentages ranging from 0 to 100) of full sample observations that appear for which weekly homework hours data is available, separately for each country-by-urbanicity cell.

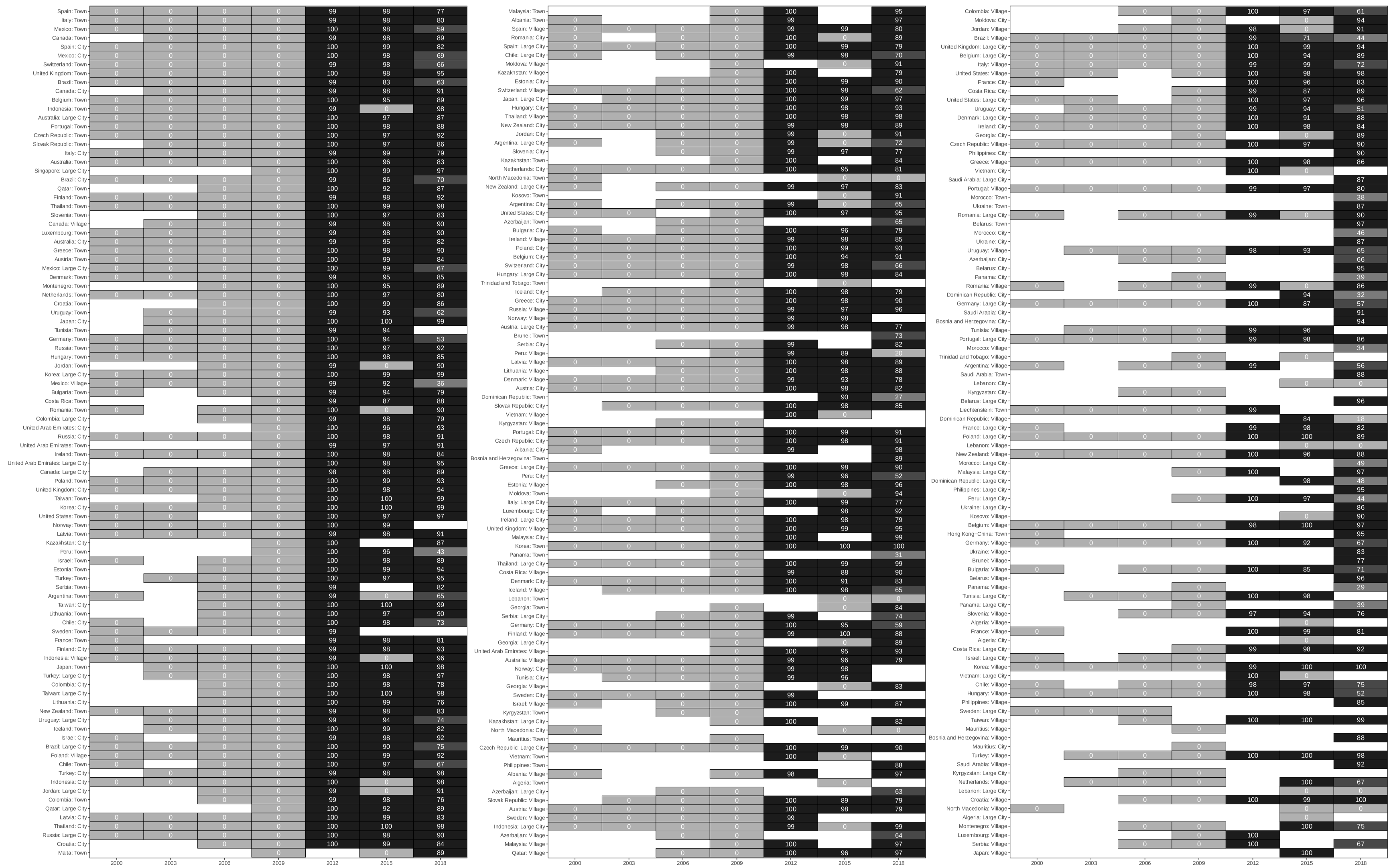

Figure C.3: Days Skipped Past 2 Weeks: Data Availability by Country and Year

Note: Figure displays the share (in percentages ranging from 0 to 100) of full sample observations that appear for which days skipped past 2 weeks data is available, separately for each country-by-urbanicity cell.

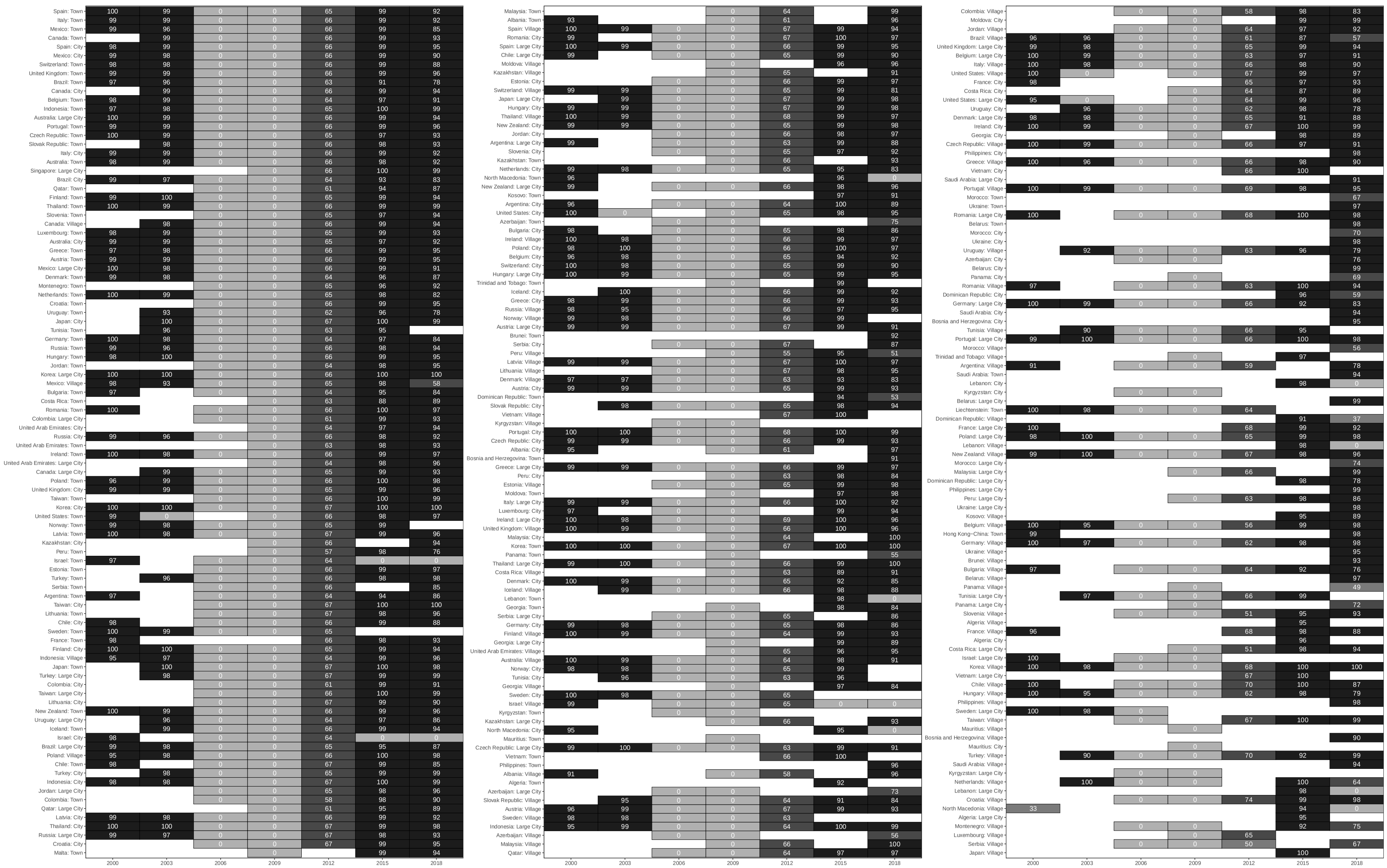

Figure C.4: Friendship Index: Data Availability by Country and Year

Note: Figure displays the share (in percentages ranging from 0 to 100) of full sample observations that appear for which friendship index data is available, separately for each country-by-urbanicity cell.

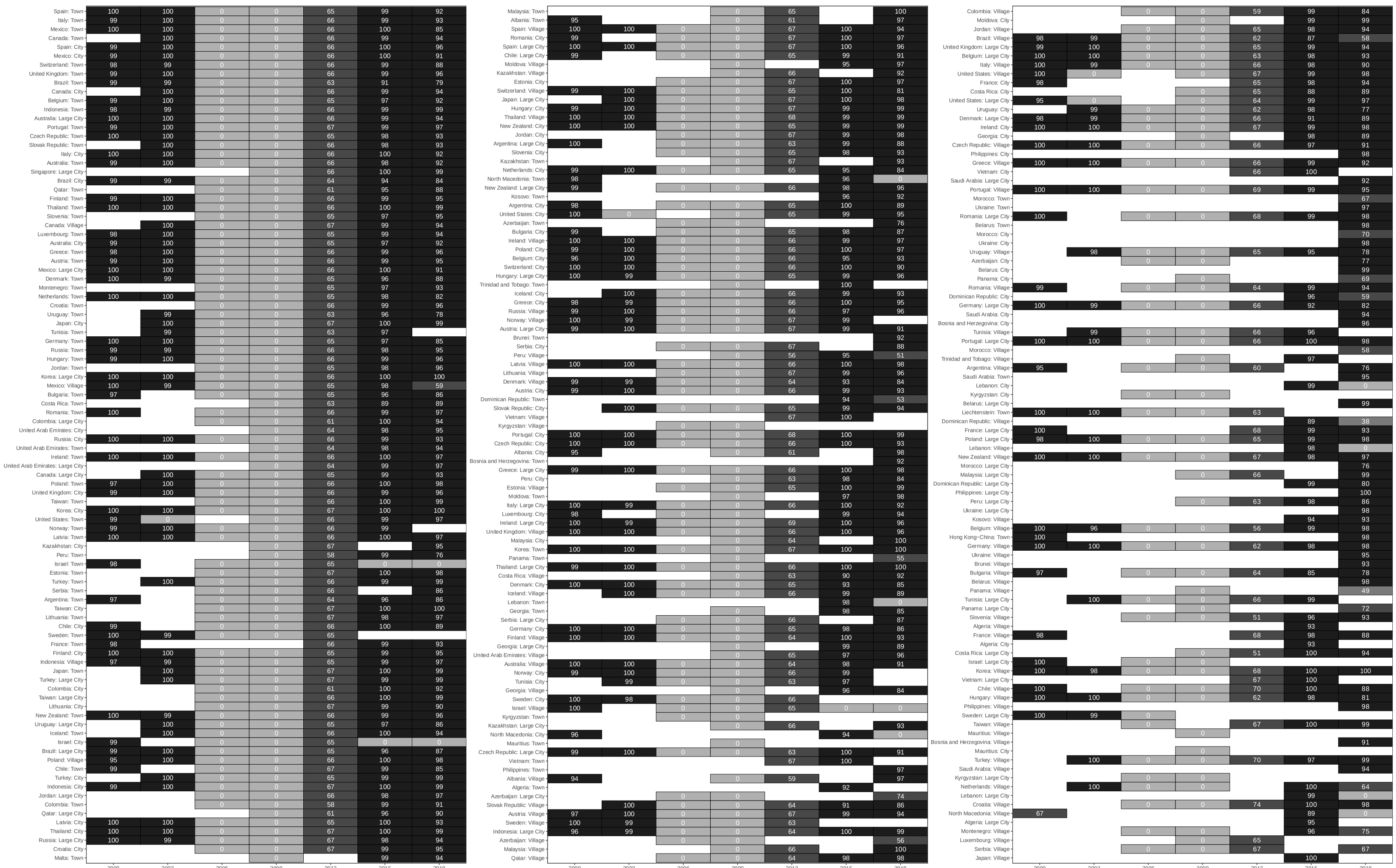

Figure C.5: Belonging Index Data Availability by Country and Year

Note: Figure displays the share (in percentages ranging from 0 to 100) of full sample observations that appear for which belonging index data is available, separately for each country-by-urbanicity cell.

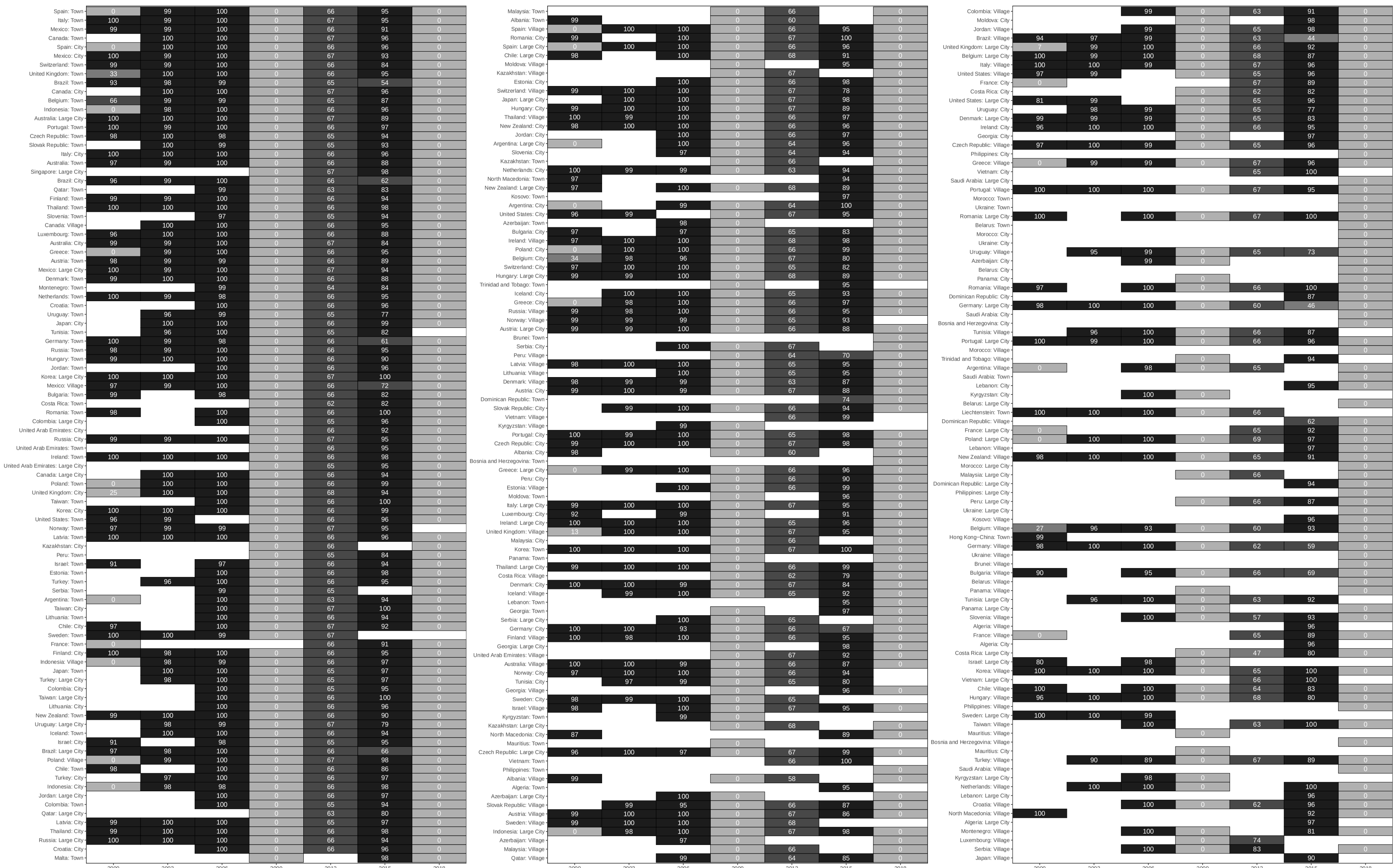

Figure C.6: Self-Efficacy Index Data Availability by Country and Year

Note: Figure displays the share (in percentages ranging from 0 to 100) of full sample observations that appear for which self-efficacy index data is available, separately for each country-by-urbanicity cell.

Table C.1: IV Estimates: Effect of 3G on Technology Access and Use

	(1)	(2)	(3)
	FS	RF	IV
Dep. Var	3G	Tech. Use	Tech. Use
Panel A: Browses the Internet Daily			
Lightning × Year	-0.005**	-0.001	
	(0.002)	(0.001)	
2G × Year	0.007+	0.007	
	(0.004)	(0.005)	
$\hat{3G}$			0.360
			(0.234)
Num.Obs.	1435055	1435055	1435055
R2	0.895	0.250	0.241
Panel B: Has a Smartphone at Home (2012-2018)			
Lightning × Year	0.016	0.001	
	(0.010)	(0.001)	
2G × Year	0.008	0.016***	
	(0.006)	(0.002)	
$\hat{3G}$			0.124*
			(0.062)
Num.Obs.	757469	757469	757469
R2	0.904	0.115	0.114
Panel C: Has a Smartphone at Home (2012-2018; 2000, 2003 Set to 0)			
Lightning × Year	-0.004**	-0.001*	
	(0.001)	(0.001)	
2G × Year	0.009*	0.001	
	(0.003)	(0.001)	
$\hat{3G}$			0.255*
			(0.116)
Num.Obs.	959418	959418	959418
R2	0.963	0.799	0.798
Panel D: Average Daily Internet Use in Minutes (2012-2018)			
Lightning × Year	0.016	0.751	
	(0.010)	(0.735)	
2G × Year	0.008	2.760	
	(0.006)	(2.051)	
$\hat{3G}$			56.847
			(39.430)
Num.Obs.	757469	757469	757469
R2	0.904	0.125	0.125
Country-by-Urbanicity FEs	✓	✓	✓
Year FEs	✓	✓	✓
Baseline Controls	✓	✓	✓

Note: Table displays instrumental variables results estimating the effect of 3G coverage on technology access and use. Column 1 displays the first stage results. Column 2 displays reduced form results. Column 3 displays two-stage least squares results. Dependent variables in Columns 2 and 3 are indicated in panel labels. The dependent variable in Column 1 is 3G coverage. Baseline controls include student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C.2: IV Estimates: Effect of 3G on PISA Test Scores (Lightning Instrument Only)

	(1)	(2)	(3)	(4)
	OLS	FS	RF	IV
Dep. Var	Score	3G	Score	Score
Panel A: Math				
3G	-0.031			
	(0.029)			
Lightning × Year		-0.007***	0.003+	
		(0.002)	(0.001)	
$\hat{3G}$				-0.361+
				(0.211)
Num.Obs.	2286455	2286455	2286455	2286455
R2	0.373	0.863	0.373	0.370
Panel B: Reading				
3G	-0.056+			
	(0.032)			
Lightning × Year		-0.007***	0.001	
		(0.002)	(0.001)	
$\hat{3G}$				-0.142
				(0.180)
Num.Obs.	2286455	2286455	2286455	2286455
R2	0.344	0.863	0.344	0.344
Panel C: Science				
3G	-0.019			
	(0.024)			
Lightning × Year		-0.007***	0.002*	
		(0.002)	(0.001)	
$\hat{3G}$				-0.322+
				(0.167)
Num.Obs.	2286455	2286455	2286455	2286455
R2	0.331	0.863	0.331	0.329
Country-by-Urbanicity FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓

Note: Table displays instrumental variables results estimating the effect of 3G coverage on test scores. Column 1 displays OLS results. Column 2 displays the first stage results. Column 3 displays reduced form results. Column 4 displays two-stage least squares results. Dependent variables in Columns 1, 3, and 4 are scaled student test scores in math (Panel A), reading (Panel B), and science (Panel C). The dependent variable in Column 2 is 3G coverage. Baseline controls include student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C.3: IV Estimates: Effect of 3G on PISA Test Scores (2G Instrument Only)

	(1)	(2)	(3)	(4)
	OLS	FS	RF	IV
Dep. Var	Score	3G	Score	Score
Panel A: Math				
3G	-0.031			
	(0.029)			
2G × Year		0.010+	-0.002	
		(0.005)	(0.005)	
$\hat{3G}$				-0.199
				(0.502)
Num.Obs.	2286455	2286455	2286455	2286455
R2	0.373	0.859	0.373	0.372
Panel B: Reading				
3G	-0.056+			
	(0.032)			
2G × Year		0.010+	-0.005	
		(0.005)	(0.005)	
$\hat{3G}$				-0.510
				(0.561)
Num.Obs.	2286455	2286455	2286455	2286455
R2	0.344	0.859	0.344	0.339
Panel C: Science				
3G	-0.019			
	(0.024)			
2G × Year		0.010+	0.003	
		(0.005)	(0.004)	
$\hat{3G}$				0.296
				(0.493)
Num.Obs.	2286455	2286455	2286455	2286455
R2	0.331	0.859	0.331	0.328
Country-by-Urbanicity FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓

Note: Table displays instrumental variables results estimating the effect of 3G coverage on test scores. Column 1 displays OLS results. Column 2 displays the first stage results. Column 3 displays reduced form results. Column 4 displays two-stage least squares results. Dependent variables in Columns 1, 3, and 4 are scaled student test scores in math (Panel A), reading (Panel B), and science (Panel C). The dependent variable in Column 2 is 3G coverage. Baseline controls include student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C.4: Heterogeneous Effects of 3G on Technology Access and Use

	Browses the Internet Daily				Has a Smartphone at Home (2012-2018)				Has a Smartphone at Home (2012-2018; 2000, 2003 Set to 0)				Average Daily Internet Use in Minutes (2012-2018)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: By Student Gender																
3G	0.024	0.055**	0.024	0.055**	0.051	0.036	0.050	0.038	0.103**	0.113**	0.103**	0.115**	32.757***	53.078**	32.734***	53.129**
	(0.025)	(0.020)	(0.024)	(0.020)	(0.035)	(0.032)	(0.036)	(0.033)	(0.033)	(0.042)	(0.034)	(0.043)	(8.111)	(18.151)	(8.127)	(18.280)
3G × Female	0.037***	0.027+	0.032**	0.027+	0.004	-0.001	0.006	0.005	-0.001	0.015	-0.002	0.016	12.030	-20.955	8.547	-29.341
	(0.010)	(0.015)	(0.010)	(0.014)	(0.012)	(0.036)	(0.011)	(0.036)	(0.010)	(0.016)	(0.009)	(0.016)	(9.577)	(20.149)	(9.420)	(20.011)
Num.Obs.	1435055	1435055	1435055	1435055	757469	757469	757469	757469	959418	959418	959418	959418	757469	757469	757469	757469
R2	0.252	0.273	0.253	0.275	0.115	0.125	0.119	0.129	0.799	0.803	0.800	0.804	0.129	0.136	0.137	0.143
Panel B: By Parental Education																
3G	0.090**	0.111***	0.092**	0.111***	0.038	0.040	0.042	0.042+	0.106*	0.138**	0.109*	0.140**	30.961**	30.063	31.703**	29.965
	(0.028)	(0.024)	(0.028)	(0.024)	(0.034)	(0.024)	(0.036)	(0.025)	(0.042)	(0.048)	(0.043)	(0.048)	(9.770)	(19.120)	(9.972)	(19.298)
3G × Either Parent has Tert. Ed.	-0.106***	-0.086***	-0.112***	-0.082**	0.015	-0.041	0.012	-0.046	-0.037	-0.085*	-0.040	-0.091*	14.741	-4.387	12.777	-10.769
	(0.020)	(0.025)	(0.021)	(0.026)	(0.018)	(0.033)	(0.018)	(0.032)	(0.036)	(0.038)	(0.036)	(0.039)	(9.289)	(20.579)	(9.567)	(20.299)
Num.Obs.	1435055	1435055	1435055	1435055	757469	757469	757469	757469	959418	959418	959418	959418	757469	757469	757469	757469
R2	0.252	0.274	0.254	0.275	0.119	0.128	0.119	0.129	0.800	0.804	0.800	0.804	0.131	0.137	0.138	0.144
Panel C: By Country Income Level																
3G	0.114**	0.113***	0.109**	0.112***	0.059+	0.036	0.059+	0.037	0.079*	0.130**	0.078*	0.133**	40.333***	47.395**	40.450***	47.795**
	(0.041)	(0.024)	(0.040)	(0.025)	(0.032)	(0.027)	(0.033)	(0.030)	(0.034)	(0.050)	(0.036)	(0.050)	(10.353)	(17.501)	(10.496)	(17.965)
3G × Country is High Income in 2000	-0.181**	-0.132***	-0.175**	-0.125***	0.009	-0.014	-0.010	-0.016	-0.027	-0.078	-0.023	-0.074	-8.123	-41.741	-2.749	-41.745
	(0.059)	(0.031)	(0.058)	(0.031)	(0.102)	(0.058)	(0.101)	(0.061)	(0.071)	(0.054)	(0.073)	(0.054)	(67.047)	(48.986)	(67.913)	(49.723)
Num.Obs.	1435055	1435055	1435055	1435055	757469	757469	757469	757469	959418	959418	959418	959418	757469	757469	757469	757469
R2	0.253	0.272	0.251	0.269	0.116	0.126	0.112	0.122	0.799	0.803	0.799	0.803	0.130	0.136	0.133	0.139
Country-by-Urbanicity FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country-by-Year FEs		✓		✓		✓		✓		✓		✓		✓		✓
Controls Interacted with Country-by-Urbanicity			✓	✓			✓	✓			✓	✓			✓	✓
Complete Interactions with Heterogeneous Variable	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: Table displays OLS results estimating the heterogeneous effect of 3G coverage on technology access and use. Dependent variables are indicated above column numbers. Baseline controls include student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend. All models include full interactions with the heterogeneous variable identified in each panel. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C.5: Heterogeneous Effects of 3G on PISA Test Scores

	Math				Reading				Science			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: By Student Gender												
3G	-0.021	-0.070**	-0.014	-0.070*	-0.049	-0.030	-0.041	-0.031	-0.008	-0.056*	0.001	-0.056*
	(0.029)	(0.026)	(0.030)	(0.029)	(0.034)	(0.026)	(0.035)	(0.028)	(0.027)	(0.024)	(0.028)	(0.026)
3G × Female	-0.015	-0.029	-0.025	-0.024	-0.010	-0.037	-0.020	-0.034	-0.016	-0.046+	-0.026	-0.045+
	(0.015)	(0.025)	(0.018)	(0.027)	(0.018)	(0.024)	(0.021)	(0.026)	(0.017)	(0.024)	(0.021)	(0.026)
Num.Obs.	2286455	2286455	2286455	2286455	2286455	2286455	2286455	2286455	2286455	2286455	2286455	2286455
R2	0.375	0.386	0.367	0.377	0.348	0.360	0.339	0.350	0.334	0.344	0.325	0.334
Panel B: By Parental Education												
3G	-0.042	-0.094***	-0.026	-0.085**	-0.071*	-0.059*	-0.058+	-0.049+	-0.022	-0.096***	-0.006	-0.086***
	(0.030)	(0.027)	(0.031)	(0.028)	(0.031)	(0.025)	(0.032)	(0.026)	(0.024)	(0.023)	(0.025)	(0.025)
3G × Either Parent has Tert. Ed.	0.036	0.042	0.009	0.031	0.041	0.040	0.020	0.030	0.012	0.049+	-0.012	0.042
	(0.031)	(0.029)	(0.030)	(0.029)	(0.030)	(0.031)	(0.029)	(0.029)	(0.025)	(0.028)	(0.024)	(0.028)
Num.Obs.	2286455	2286455	2286455	2286455	2286455	2286455	2286455	2286455	2286455	2286455	2286455	2286455
R2	0.379	0.391	0.380	0.391	0.351	0.363	0.339	0.351	0.338	0.348	0.339	0.349
Panel C: By Country Income Level												
3G	-0.029	-0.116***	-0.036	-0.116***	-0.047	-0.069**	-0.050	-0.069*	-0.066*	-0.093***	-0.071*	-0.093**
	(0.031)	(0.029)	(0.033)	(0.032)	(0.039)	(0.026)	(0.041)	(0.030)	(0.029)	(0.027)	(0.031)	(0.030)
3G × Country is High Income in 2000	0.046	0.099*	0.027	0.089+	0.047	0.068	0.023	0.048	0.065	0.043	0.047	0.033
	(0.090)	(0.049)	(0.080)	(0.047)	(0.090)	(0.051)	(0.079)	(0.048)	(0.071)	(0.046)	(0.062)	(0.043)
Num.Obs.	2286455	2286455	2286455	2286455	2286455	2286455	2286455	2286455	2286455	2286455	2286455	2286455
R2	0.375	0.384	0.369	0.378	0.346	0.357	0.327	0.338	0.334	0.342	0.330	0.338
Country-by-Urbanicity FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country-by-Year FEs		✓		✓		✓		✓		✓		✓
Controls Interacted with Country-by-Urbanicity			✓	✓			✓	✓			✓	✓
Complete Interactions with Heterogeneous Variable	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: Table displays OLS results estimating the heterogeneous effect of 3G coverage on test scores. Dependent variables are scaled student test scores in math, reading, and science. Baseline controls include student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend. All models include full interactions with the heterogeneous variable identified in each panel. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C.6: Heterogeneous Effects of 3G on Social Well-Being and Mental Health

	Friendship Index (2000-2003, 2012-2018)				Belonging Index (2000-2003, 2012-2018)				Self-Efficacy Index (2000-2006, 2012-2015)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: By Student Gender												
3G	0.023	-0.043	0.025	-0.038	-0.023	-0.024	-0.020	-0.017	0.000	-0.056	0.002	-0.059
	(0.050)	(0.034)	(0.050)	(0.034)	(0.068)	(0.034)	(0.068)	(0.036)	(0.056)	(0.040)	(0.057)	(0.044)
3G × Female	-0.064*	-0.089	-0.053+	-0.080	-0.047	-0.051	-0.041	-0.062	0.032	0.044	0.024	0.053
	(0.027)	(0.055)	(0.030)	(0.056)	(0.034)	(0.042)	(0.038)	(0.043)	(0.029)	(0.045)	(0.027)	(0.048)
Num.Obs.	1318338	1318338	1318338	1318338	1325812	1325812	1325812	1325812	1194178	1194178	1194178	1194178
R2	0.035	0.044	0.038	0.047	0.042	0.058	0.044	0.059	0.059	0.078	0.054	0.073
Panel B: By Parental Education												
3G	0.001	-0.058+	0.004	-0.053+	-0.056	-0.010	-0.050	-0.001	-0.026	-0.075*	-0.028	-0.070+
	(0.043)	(0.030)	(0.043)	(0.031)	(0.046)	(0.037)	(0.045)	(0.038)	(0.065)	(0.038)	(0.065)	(0.039)
3G × Either Parent has Tert. Ed.	-0.017	-0.057	-0.021	-0.066	0.036	-0.054	0.028	-0.085	0.097*	0.095*	0.103*	0.098*
	(0.054)	(0.054)	(0.051)	(0.056)	(0.064)	(0.067)	(0.059)	(0.070)	(0.048)	(0.041)	(0.048)	(0.046)
Num.Obs.	1318338	1318338	1318338	1318338	1325812	1325812	1325812	1325812	1194178	1194178	1194178	1194178
R2	0.034	0.043	0.038	0.046	0.041	0.056	0.046	0.060	0.057	0.076	0.058	0.077
Panel C: By Country Income Level												
3G	0.030	-0.123***	0.031	-0.118***	0.009	-0.083*	0.011	-0.075+	-0.039	-0.100*	-0.049	-0.094*
	(0.047)	(0.024)	(0.047)	(0.025)	(0.065)	(0.037)	(0.065)	(0.038)	(0.062)	(0.043)	(0.064)	(0.048)
3G × Country is High Income in 2000	-0.115	0.193**	-0.104	0.193**	-0.204	0.204**	-0.223	0.160**	0.175	0.187**	0.185	0.191**
	(0.095)	(0.060)	(0.092)	(0.063)	(0.208)	(0.062)	(0.204)	(0.059)	(0.123)	(0.059)	(0.125)	(0.065)
Num.Obs.	1318338	1318338	1318338	1318338	1325812	1325812	1325812	1325812	1194178	1194178	1194178	1194178
R2	0.034	0.042	0.036	0.043	0.040	0.054	0.042	0.056	0.057	0.074	0.055	0.071
Country-by-Urbanicity FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Country-by-Year FEs		✓		✓		✓		✓		✓		✓
Controls Interacted with Country-by-Urbanicity			✓	✓			✓	✓			✓	✓
Complete Interactions with Heterogeneous Variable	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Note: Table displays OLS results estimating the heterogeneous effect of 3G coverage on social well-being and mental health. Dependent variables are indices with a mean of 0 and a standard deviation of 1. Baseline controls include student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend. All models include full interactions with the heterogeneous variable identified in each panel. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. These variables are not available for all countries in all years; see Appendix Figures C.4, C.5, and C.6. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C.7: Heterogeneous Effects of 3G on Homework and Absenteeism

	Weekly Homework Hours (2000-2006, 2012)				Days Skipped Past 2 Weeks (2012-2018)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: By Student Gender								
3G	0.850***	0.292	0.877***	0.284	0.431***	0.054	0.432***	0.059
	(0.231)	(0.183)	(0.227)	(0.187)	(0.092)	(0.088)	(0.092)	(0.088)
3G × Female	0.263	0.418+	0.248	0.503*	-0.028	-0.027	-0.028	-0.058
	(0.163)	(0.215)	(0.167)	(0.226)	(0.103)	(0.121)	(0.104)	(0.117)
Num.Obs.	792899	792899	792899	792899	1124738	1124738	1124738	1124738
R2	0.141	0.166	0.146	0.170	0.115	0.131	0.119	0.134
Panel B: By Parental Education								
3G	0.844**	0.510*	0.850**	0.536*	0.420***	-0.087	0.414***	-0.098
	(0.268)	(0.212)	(0.264)	(0.216)	(0.083)	(0.075)	(0.083)	(0.075)
3G × Either Parent has Tert. Ed.	0.203	-0.095	0.292	-0.057	0.031	0.209+	0.040	0.208+
	(0.248)	(0.262)	(0.248)	(0.267)	(0.097)	(0.109)	(0.097)	(0.112)
Num.Obs.	792899	792899	792899	792899	1124738	1124738	1124738	1124738
R2	0.139	0.163	0.139	0.162	0.114	0.129	0.118	0.133
Panel C: By Country Income Level								
3G	1.066**	0.303	1.114**	0.398+	0.310**	-0.062	0.309**	-0.062
	(0.372)	(0.223)	(0.370)	(0.232)	(0.109)	(0.075)	(0.109)	(0.074)
3G × Country is High Income in 2000	-0.491	0.543	-0.469	0.496	0.495	0.325	0.520	0.318
	(0.577)	(0.335)	(0.573)	(0.342)	(0.445)	(0.215)	(0.443)	(0.217)
Num.Obs.	792899	792899	792899	792899	1124738	1124738	1124738	1124738
R2	0.137	0.160	0.135	0.158	0.114	0.127	0.115	0.128
Country-by-Urbanicity FEs	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓
Country-by-Year FEs		✓		✓		✓		✓
Controls Interacted with Country-by-Urbanicity			✓	✓			✓	✓
Complete Interactions with Heterogeneous Variable	✓	✓	✓	✓	✓	✓	✓	✓

Note: Table displays OLS results estimating the heterogeneous effect of 3G coverage on homework and absenteeism. Dependent variables are indicated above column numbers. Baseline controls include student gender, age, immigrant status, fixed effects for private (with government funding) and private (without government funding) school attendance, mother's and father's education level, and 2000 GDP per capita interacted with a time trend. All models include full interactions with the heterogeneous variable identified in each panel. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ic} / \sum_{i \in c} w_{ic}$, where w_{ic} is individual i in country c's sampling weight, and $\sum_{i \in c} w_{ic}$ denotes the sum of sampling weights in country c. These variables are not available for all countries in all years; see Appendix Figures C.2 and C.3. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.