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 2.5 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. Changes in 3G coverage lead to significant declines in test scores in math, science, and reading, with magnitudes roughly equivalent to the loss of one-quarter of a year of learning. We also find evidence of a reduction in the ease of making friends and a sense of belonging.

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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, UNICEF estimates that one in three internet users is a child (UNICEF, 2019).[2] Adolescence is a crucial time for human capital development (Cunha and Heckman, 2007); how have these massive changes in adolescents' behavior and environment affected their development of skills?

The answer to this question is ambiguous. On one hand, information technology can broaden access to information and resources that enhance student learning (The Economist, 2017). Conversely, these technologies may have adverse effects on mental health, sleep, and various other facets of students' lives, which could impede their learning and skill development (Braghieri et al., 2022; Billari et al., 2018; Golin, 2022). Allcott et al. (2022) argue that a model of "digital addiction," in which habit formation and self-control problems play a large role in use of digital technologies, may explain these facts. More broadly, Pritchett (2022) argues that the massive increase in computing power coupled with relatively unimpressive test score growth suggests that digitization is not a "key element of improving learning in schools." This study investigates the impact of 3G internet, a mobile network technology that provides wireless internet connectivity, on the human capital development of adolescents.[3]

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 2.5 million students from the Programme for International Student Assessment (PISA), an international assessment conducted by the Organisation for Economic Co-operation and Development (OECD). PISA measures the skills of 15-year-old students in reading, mathematics, and science, allowing us to measure changes in adolescent skill development across regions and time. PISA data enable us to explore the relationship between 3G coverage, internet access and use, and student test scores over nearly two decades and across multiple countries.

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

[2] This estimate is based on a "survey results of 11 countries, from across which more than 14,000 internet-using children were interviewed about their online experiences."

[3] While both 3G and its predecessor, 2G, provide basic voice and text communication services, 3G networks offer faster data speeds, increased data capacity, and enhanced support for multimedia applications such as online gaming and video calling.

In this context, we find evidence that expansions in 3G lead to large increases in student technology use. Students living in areas with 3G coverage are 4 percentage points more likely to browse the internet daily, are 10 percentage points more likely to have a smartphone at home, and report spending an additional 5 hours on the internet each week. In turn, 3G expansion results in reductions in student test score performance. The magnitude of these reductions—approximately 0.04 to 0.08 standard deviations—is on par with roughly one-quarter of a year of 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. We also find evidence that measures of social connectedness and mental well-being —namely, ease of making friends and feeling a sense of belonging—worsen after the arrival of 3G.

This research contributes to the literature on exposure to communications technology and the development of human capital. Gentzkow and Shapiro (2008) provide historical evidence that television exposure during pre-schooling years had small positive effects on adolescent test scores in the United States. However, exposure to more recent waves of communications technologies has generally been associated with decreases or negligible impacts on test scores. Namely, Malamud and Pop-Eleches (2011) provide quasi-experimental evidence that home computer use causes lower academic test scores in Romania. Fairlie and Robinson (2013) present the results of an experiment in the United States providing free home computers to students, and find precise null effects on a range of academic outcomes among adolescents. Vigdor et al. (2014) study the rollout of high-speed internet in North Carolina, and find that students who gain access to high-speed internet exhibit small but persistent reductions in test scores. Similarly, Malamud et al. (2019) find providing students access to laptops with free internet did not affect test scores in Peru. Finally, 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.

Some targeted educational technology interventions, such as the remedial technology-aided after-school program studied in Muralidharan et al. (2019) or the text-based parental engagement intervention in Doss et al. (2019), have been shown to generate significant gains in student test score performance. Escueta et al. (2020) review this literature more broadly, highlighting computer-assisted learning and technology-enabled behavioral interventions as "two areas that show considerable promise."

Beyond the educational realm, this research contributes to the nascent and growing body of research examining the socioeconomic and political impacts of expanding internet access. Previous studies have linked broadband internet access to the widening of the mental health gender gap among young women (Golin, 2022; Donati et al., 2022), increased distractions and lower sleep quality (Billari et al., 2018), increased employment (Hjort and Poulsen, 2019) and reduced social capital (Geraci et al., 2022). Recent studies on 3G internet suggest that its expansions increased the rate of child injuries (Palsson, 2017), led to changes in political views and voting behavior (Guriev et al., 2021; Melnikov, 2021; Falck et al., 2014; Golin and Romarri, 2022), and increased labor force participation among women (Chiplunkar and Goldberg, 2022).

Our study distinguishes itself from prior work by investigating the influence of a recent and significant technological advancement— *mobile* internet—on human capital development on a global scale. While most of the previous studies have focused on the impact of broadband internet access on student outcomes, our study examines the effects of wireless mobile internet, which has become increasingly pervasive, particularly among adolescents, coinciding with the rise in smartphone ownership. For instance, we show that close to 90% of students in PISA data reported having a smartphone at home between 2012 and 2018. Leveraging large-scale, cross-country data from PISA offers distinct benefits compared to prior studies. First, our setting allows us to capture the general equilibrium impacts of expanding internet access. These impacts may be particularly important in the presence of social externalities associated with internet access generally and social media specifically (Bursztyn et al., 2023). Second, our setting allows us to measure the diverse effects of internet use across low-, middle- and high-income countries. This global perspective is invaluable for policymakers striving to bridge the digital divide and devise effective strategies for digital inclusion (United Nations, 2019). Finally, our data allows us to quantify the effects of internet use on various aspects of students' lives—technology use, social connectedness, well-being, homework, and absenteeism—during adolescence, a crucial period for human capital development.

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.[4] 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."[5] We use student-level PISA data from seven rounds of testing between 2000 to 2018.[6]

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."[7] 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 B. We make a small number of sample restrictions; we exclude students with missing test scores in any subjects, students with missing data on age, gender, or urbanicity, and students who are below 13 years old or above 17 years old.[8]

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 re-

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

[5] PISA 2018 Technical Report, Chapter 4.

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

[7] What is PISA?, About PISA.

[8] These restrictions on age, gender, and urbanicity lead us to drop 5 percent of observations with non-missing test scores. Most of these observations are dropped due to missing urbanicity data (which is necessary for our research design); among observations with non-missing urbanicity, only 0.06 percent (6 in 10,000) observations are dropped.

sponses are village, town, city, or large city. We refer to this variable as urbanicity. We use this variable, in combination with the geospatial data described below, to capture student exposure to 3G coverage over time. Appendix Figure F.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 B details how we harmonize measures across PISA rounds. In addition, Appendix Figures F.3 to F.8 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 2.6 million and 1.5 million student-level observations, respectively. Appendix Figure F.2 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 A.1 illustrates this process among five large countries in our sample: Australia, Canada, Italy, Mexico, and Spain.

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, organized into 1 by 1-kilometer grid cells, that indicate which areas of each country have 3G coverage.

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.[9])

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 kilometer that do not fall in a city or large city—are treated as towns.

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 gridded points that have 3G, weighted by the total population. 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.[10]

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

[10] This data is sourced from the OECD (OECD, 2004) and public press releases accompanying the introduction of 3G. 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:

With these data, we estimate 3G coverage monthly 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. To calculate lightning frequency, 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 Descriptive Statistics

2.3.1 Summary Statistics

Table A.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) are roughly 0.58. This figure is larger—0.61—for the ICT sample in Panel B.

Both panels additionally summarize a set of variables related to homework, attendance, social connectedness, and well-being. As noted above, these questions were not administered universally across countries and PISA rounds; Appendix Figures F.3 to F.8 summarize annual missingness by country-by-urbanicity pair for variables for which full data is not available.

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.

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 reported weekly hours spent on the internet was 29.4, or roughly 4 hours per day.

2.3.2 Trends in Internet Usage and Scores Over Time

Figure A.2 shows over-time trends among OECD countries for 3G coverage, test scores, and other measures of technology access and use.[11] After increasing between 2000 and 2009, student test scores in math, reading, and science declined between 2009 and 2018. These test score declines occurred after a rapid expansion in 3G coverage between 2003 and 2009, which accompanied large changes in students' reported internet access and use.

Figure A.3 displays our estimated 3G coverage at the country level for 2006 and 2018. In line with the global trends depicted in Figure A.2, the top panel of Figure A.3 shows that in 2006, only a small portion of the population in the sample countries had 3G access. By 2018, as shown in the bottom panel, nearly every country in our sample had over 75 percent of their population covered by 3G

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, Appendix Table E.1 displays the observed relationship between test scores and various measures of technology use in PISA data from 2012, 2015, and 2018.The results in Appendix E.1 demonstrate that the associative relationships between technology use and test scores vary substantially across different measures of technology use. Specifically, reported internet use in hours is associated with significantly lower test scores, while smartphone ownership and daily internet browsing are associated with higher scores. 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,

[11] Sample countries in Figure A.2 are the OECD 23; the 23 countries with non-missing test scores in PISA exams from 2003 to 2022 and the set of countries used in the most recent OECD PISA Publications (2022). To construct the figure, we calculated country-level averages of each variable in each year, weighted by PISA sampling weights. Points in Figure A.2 reflect the average of these average country-level values in each year.

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 differences in test scores across areas with and without 3G coverage over time. Our baseline two-way fixed effects specification is below.

$$y_{icut} = \gamma 3G_{cut} + X_{icut}\theta + \phi_{cu} + \kappa_{ut} + \tau_{ct} + \varepsilon_{icut} \tag{1}$$

where i indexes students, c indexes countries, u indicates urbanicity, and t indexes years. We include fixed effects for country-by-urbanicity (ϕ_{cu}) so our estimates reflect changes in within-country differences over time, rather than differences between areas that precede the arrival of 3G. By including country-by-year fixed effects (τ_{ct}), our estimates reflect the effect of within-country over-time variation in 3G coverage rather than other factors that may vary differentially across countries and time such as education policies (e.g. curriculum changes) or economic policies (e.g. education budgets). Additionally, including urbanicity-by-year fixed effects (κ_{ut}) controls for any factors that may vary over time within urban and rural settings such as demographic trends, educational resources or funding, and economic factors such as employment opportunities.

Our set of baseline controls, X_{icut}, include student gender, age, and immigration status, whether the student's school is public, private with government funding, or private without government funding, mother's and father's education level, and dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type.[12] 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 in the same country.

[12] When father's or mother's education is missing, we replace these observations with the mean.

For all regressions, we cluster standard errors at the country-by-urbanicity level. In addition, to account for PISA's sampling regime, we weight each observation by $w_{ict} / \sum_{i \in ct} w_{ict}$, where w_{ict} is individual i in country c in year t's sampling weight, and $\sum_{i \in ct} w_{ict}$ denotes the sum of sampling weights in country c in year t.

3.2 Two-Stage Difference-in-Difference Estimates

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 from the typical two-way fixed effects estimator, 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 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 C.

3.3 Instrumental Variables Estimates

While our main estimates are those in the difference-in-differences specification described above, we note that many prior researchers have used instrumental variables estimation to estimate the effect of 3G coverage on various outcomes. In the literature, two instruments have been used most extensively: local lightning strike frequency (Manacorda and Tesei, 2020; Chiplunkar and Goldberg, 2022; Guriev et al., 2021; Jiang et al., 2022) and prior 2G coverage (Harm Adema et al., 2022). The logic behind these two instruments is as follows. First, 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. 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 provide additional details and results in Appendix D, noting that our data lacks the geographical precision when compared to other papers that have used these instruments previously. For example, the data used in Manacorda and Tesei (2020) includes 10,409 unique geographic cells, and the data used in Guriev et al. (2021) includes 2,232 international subregions. By comparison, our main test score data includes 291 unique country-by-urbanicity combinations. Consequently, the relatively small number of geographic cells in our data renders our instrumental variables estimates less precise compared to studies with more granular geographical data.

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.

4.1 Effects on Technology Access and Use

Table A.2 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 1.6 million student-level observations, slightly more than half of our full sample. Throughout, regressions in Column 1 include country-by-urbanicity, urbanicity-by-year, and country-by-year fixed effects, in addition to our set of baseline controls. Regressions in Column 2 additionally include interactions between all baseline controls and country-by-urbanicity fixed effects. Intuitively, the addition of these interaction terms allows the effect of student demographics (e.g. gender, age) to vary across geographies.

Panel A of Table A.2 reports effects on the likelihood that students report browsing the internet daily. Estimates indicate that 3G coverage is associated with a 4 percentage-point increase in the likelihood of daily internet browsing. These estimates are economically significant; the sample mean in Table A.1 is roughly 0.53.

Panels B and C of Table A.2 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 B, are very imprecise and statistically insignificant, but point estimates suggest that 3G coverage increases smartphone ownership by roughly 4 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 C, are much larger and suggest that 3G coverage increases smartphone ownership by 10 percentage points.

Finally, Panel D of Table A.2 shows estimates on weekly 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 report spending on the internet. Effect sizes are reasonably large across specifications, suggesting that 3G coverage increases time on the internet by 5 hours weekly or roughly 40 minutes daily. PISA data additionally allows us to distinguish between reported time spent on the internet in and out of school. Appendix Table E.2 reports results separately for these two measures, indicating that 3G is associated with a 4-hour increase in reported weekly internet use out of school. Effects on internet use in school are not statistically significant.

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 A.3 shows OLS estimates of the effect of 3G coverage on test scores. Panels A, B, and C report effects on math, reading, and science scores, respectively. Similar to the results in Table A.2, Columns 1 and 2 differ in their inclusion of interactions between all baseline controls and country-by-urbanicity fixed effects.

Across both specifications in all subjects, the estimated effects of 3G access on test scores are negative. Focusing on the effects in Column 2, which include the most expansive set of controls, we find that 3G coverage leads to reductions in math scores of roughly 0.07 standard deviations ($p < 0.01$). Our estimates for reading and science show slightly smaller declines of 0.05 ($p < 0.05$) and 0.04 ($p < 0.1$) standard deviations, respectively. Our results are consistent with Vigdor et al. (2014), which also finds that the negative test score effects of high-speed internet access are larger in math (0.027 standard deviations, $p < 0.05$) than in reading (0.01 standard deviations, $p > 0.1$).

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.[13] Our estimates fall between one-sixth and just over a third of these estimates.

Test Score Effects in the ICT Sample

Our main test score results in Table A.3 use our full sample. In Appendix Table E.3, we show that we obtain similar test score results if we restrict ourselves to using the ICT sample, that is, those students for whom we have measures of internet use and access.

4.2.2 Robustness

We subject our main estimates on technology access and use and test scores to a set of robustness checks. These are briefly described below.

Two-Stage Difference-in-Differences Results

In Appendix C, we repeat our difference-in-differences analyses using the two-stage difference-in-differences estimator proposed by Gardner et al. (2023), which is robust to potential bias associated with two-way fixed effects estimation. (As described further in Appendix C, we perform these analyses on data collapsed at the country-by-urbanicity-by-year level to simplify computation.) For effects on smartphone ownership and browsing frequency, we obtain similar results when using this estimator.[14] With respect to test scores, our estimates are consistently negative and

[13] Bloom et al. (2008) use nationally representative data from the United States. 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.

[14] Due to limited data availability, we are unable to estimate effects on the length of daily internet use using this method.

slightly larger than our difference-in-differences results. We obtain similar results when we limit our sample to the set of country-by-urbanicity pairs that appear in all 6 PISA rounds between 2003 and 2018, which we refer to as the "balanced sample."

Additionally, these estimates allow us to estimate event studies, which 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.

Instrumental Variables Estimates

We describe our instrumental variables methodology and results in Appendix D. Broadly, our estimates for effects on technology access and use are similar in size but less precise than the difference-in-differences effects. With respect to test scores, our instrumental variables estimates are slightly larger—between -0.1 and -0.3 standard deviations—but much less precise: 90% confidence intervals include zero for all subjects.

4.3 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.[15]

Appendix Tables E.4 and E.5 display our results concerning technology access and use and test scores, respectively. With respect to gender and test scores, we find some suggestive evidence for a larger negative response among female students. Coefficients on 3G $\times$ Female interaction terms fall between 0 and -0.06, but are generally 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.

On parental education, our results are also 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.

[15] PISA does not collect data on individual students' prior test scores, so we are unable to test for heterogeneity with respect to prior test scores.

In other words, test scores for students coming from less educated families are more negatively affected by the presence of 3G coverage. These effects raise the possibility that more highly educated families may be better equipped to shield their children from the negative effects of technology.

Finally, 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. First, it is possible that these non-high-income countries are those for which 3G had significant effects on internet access and use, while high-income countries expanded internet access and use among adolescents before the arrival of 3G. Alternatively, these differences may capture differences in teachers' and parents' ability to utilize technology productively for educational purposes.[16] Finally, differences across countries could simply reflect better parental awareness of the potential downsides of internet connectivity and stronger supervision of technology use at home in high-income countries.[17]

4.4 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 E.4, we show that these three groups also exhibit the largest increases in daily internet browsing. While not definitive, these results are consistent with the possibility that direct

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

[17] For example, Ramey and Ramey (2010) document large increases in time spent on childcare among parents in the United States and Canada in the mid-1990s.

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 well-being among students in our sample. The availability of these measures is somewhat limited—Appendix Figures F.3 to F.8 display their availability across countries and PISA survey rounds—so these relationships should be interpreted cautiously.

Panels A, B, and C of Table A.4 test whether 3G coverage is associated with changes in measures of social connectedness and well-being. 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. Effects on all three indices are negative and range between 0.05 to 0.16 standard deviations. As a point of reference, Braghieri et al. (2022) estimate that the arrival of Facebook on college campuses reduced a 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. Fletcher (2010) find large effects of depressive symptoms on educational attainment, controlling for sibling fixed effects, supporting the notion that worsened mental well-being may affect student learning outcomes.

Another potential mechanism through which 3G could lower student learning is through lower engagement with school work. The arrival of mobile internet potentially changes both the opportunity cost of studying as well as the productivity of study time. Both of these effects may lead students to alter their homework time in response to the arrival of 3G coverage. Panels D, E, and F of Table A.4 test whether changes in 3G coverage are associated with changes in time spent doing homework or frequency of school absences. The results in Panel D suggest that 3G coverage is associated with increases in homework time of about 20 minutes per week. This result is surprising, given that it runs contrary to the effects on test scores. However, in Panel E we find suggestive evidence that students are also slightly more likely to have skipped nearly a quarter of a school day in the last two weeks so part of the increase in homework hours could simply reflect students trying to compensate for missed classes. Panel F shows that school administrators were 3 percentage points (nearly 33%) more likely to report that students skipping classes was hindering learning "A lot" post-the arrival of 3G.[18]

To contextualize these results, we note that recent work by Brown et al. (2022) highlights the importance of cognitive endurance on academic performance, and increased distraction during homework completion (Allcott et al., 2022) could reduce the productivity of homework time. Furthermore, Lavy (2015) finds that each additional hour of instructional time per week raises test scores by an average of 0.06 standard deviations using the PISA data. Comparing our estimated effect of 3G on missed school days with this estimated impact of missing an instructional hour, we find that this channel could potentially explain around 4-6% of our estimated declines in Math, Reading, and Science, ranging from 0.04 to 0.08 standard deviations. These calculations are shown in Appendix Table E.10.

Finally, we explore the relationship between these candidate mechanisms and student demographic characteristics. However, the results (presented in Appendix Tables E.6 and E.7) do not offer strong evidence to support clear patterns of heterogeneity in the impact of 3G on social connectedness, well-being, or academic behaviors.

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, others express concerns about the adverse effects of these technologies on sleep, mental health, and other aspects of students' lives, which could impede 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. 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

[18] Appendix Table E.9 displays results with respect to other levels of perceived skipping.

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.

References

Adema, Joop Age Harm, Cevat Giray Aksoy, and Panu Poutvaara, "Mobile internet access and the desire to emigrate," 2022.

Allcott, Hunt, Matthew Gentzkow, and Lena Song, "Digital addiction," *American Economic Review*, 2022, *112* (7), 2424–2463.

Bessone, Paul, Ricardo Dahis, and Lisa Ho, "The impact of 3G mobile internet on educational outcomes in Brazil," 2020.

Billari, Francesco C, Osea Giuntella, and Luca Stella, "Broadband internet, digital temptations, and sleep," *Journal of Economic Behavior Organization*, 2018, *153*, 58–76.

Bloom, Howard S, Carolyn J Hill, Alison Rebeck Black, and Mark W Lipsey, "Performance trajectories and performance gaps as achievement effect-size benchmarks for educational interventions," *Journal of Research on Educational Effectiveness*, 2008, *1* (4), 289–328.

Braghieri, Luca, Ro'ee Levy, and Alexey Makarin, "Social media and mental health," *American Economic Review*, 2022, *112* (11), 3660–3693.

Brown, Christina L, Supreet Kaur, Geeta Kingdon, and Heather Schofield, "Cognitive endurance as human capital," Technical Report, National Bureau of Economic Research 2022.

Bursztyn, Leonardo, Benjamin R Handel, Rafael Jimenez, and Christopher Roth, "When product markets become collective traps: The case of social media," Technical Report, National Bureau of Economic Research 2023.

Chaisemartin, Clément De and Xavier d'Haultfoeuille, "Two-way fixed effects estimators with heterogeneous treatment effects," *American Economic Review*, 2020, *110* (9), 2964–2996.

Chiplunkar, Gaurav and Pinelopi Koujianou Goldberg, "The Employment Effects of Mobile Internet in Developing Countries," Report, National Bureau of Economic Research 2022.

Cunha, Flavio and James Heckman, "The technology of skill formation," *American economic review*, 2007, *97* (2), 31–47.

Donati, Dante, Ruben Durante, Francesco Sobbrio, and Dijana Zejcirovic, "Lost in the net? Broadband Internet and youth mental health," 2022.

Doss, Christopher, Erin M Fahle, Susanna Loeb, and Benjamin N York, "More than just a nudge: Supporting kindergarten parents with differentiated and personalized text messages," *Journal of Human Resources*, 2019, *54* (3), 567–603.

Escueta, Maya, Andre Joshua Nickow, Philip Oreopoulos, and Vincent Quan, "Upgrading education with technology: Insights from experimental research," *Journal of Economic Literature*, 2020, *58* (4), 897–996.

Evans, David and Fei Yuan, "Equivalent years of schooling: A metric to communicate learning gains in concrete terms," *World Bank Policy Research Working Paper*, 2019, (8752).

Fairlie, Robert W and Jonathan Robinson, "Experimental evidence on the effects of home computers on academic achievement among schoolchildren," *American Economic Journal: Applied Economics*, 2013, *5* (3), 211–240.

Falck, Oliver, Robert Gold, and Stephan Heblich, "E-lections: Voting Behavior and the Internet," *American Economic Review*, 2014, *104* (7), 2238–2265.

Feigenberg, Benjamin, Ben Ost, and Javaeria A Qureshi, "Omitted variable bias in interacted models: A cautionary tale," *Review of Economics and Statistics*, 2023, pp. 1–47.

Fletcher, Jason M, "Adolescent depression and educational attainment: results using sibling fixed effects," *Health economics*, 2010, *19* (7), 855–871.

Gardner, John, Neil Thakral, Linh T Tô, and Luther Yap, "Two-Stage Differences in Differences," 2023.

Gentzkow, Matthew and Jesse M Shapiro, "Preschool television viewing and adolescent test scores: Historical evidence from the Coleman study," *The Quarterly Journal of Economics*, 2008, *123* (1), 279–323.

Geraci, Andrea, Mattia Nardotto, Tommaso Reggiani, and Fabio Sabatini, "Broadband internet and social capital," *Journal of Public Economics*, 2022, *206*, 104578.

Golin, Marta, "The effect of broadband internet on the gender gap in mental health: Evidence from germany," *Health Economics*, 2022, *31*, 6–21.

_ **and Alessio Romarri**, "Broadband Internet and Attitudes Towards Migrants: Evidence from Spain," 2022.

Goodman-Bacon, Andrew, "Difference-in-differences with variation in treatment timing," *Journal of Econometrics*, 2021, *225* (2), 254–277.

Guriev, Sergei, Nikita Melnikov, and Ekaterina Zhuravskaya, "3g internet and confidence in government," *The Quarterly Journal of Economics*, 2021, *136* (4), 2533–2613.

Hjort, Jonas and Jonas Poulsen, "The arrival of fast internet and employment in Africa," *American Economic Review*, 2019, *109* (3), 1032–1079.

Jiang, Erica Xuewei, Gloria Yang Yu, and Jinyuan Zhang, "Bank Competition amid Digital Disruption: Implications for Financial Inclusion," *Available at SSRN 4178420*, 2022.

Kraft, Matthew A, "Interpreting effect sizes of education interventions," *Educational Researcher*, 2020, *49* (4), 241–253.

Lavy, Victor, "Do differences in schools' instruction time explain international achievement gaps? Evidence from developed and developing countries," *The Economic Journal*, 2015, *125* (588), F397–F424.

Malamud, Ofer and Cristian Pop-Eleches, "Home computer use and the development of human capital," *The Quarterly journal of economics*, 2011, *126* (2), 987–1027.

_ **, Santiago Cueto, Julian Cristia, and Diether W Beuermann**, "Do children benefit from internet access? Experimental evidence from Peru," *Journal of Development Economics*, 2019, *138*, 41–56.

Manacorda, Marco and Andrea Tesei, "Liberation technology: Mobile phones and political mobilization in Africa," *Econometrica*, 2020, *88* (2), 533–567.

Melnikov, Nikita, "Mobile internet and political polarization," *Available at SSRN 3937760*, 2021.

Muralidharan, Karthik, Abhijeet Singh, and Alejandro J Ganimian, "Disrupting education? Experimental evidence on technology-aided instruction in India," *American Economic Review*, 2019, *109* (4), 1426–1460.

OECD, "Development of Third-Generation Mobile Services in the OECD," Technical Report 85, OECD Publishing, Paris 2004.

—, "Education at a Glance 2022:Indicators, OECD," *URL: https://www.oecd-ilibrary.org/education/education-at-a-glance-2023*$_8008b7a1-en$, 2023.

Palsson, Craig, "Smartphones and child injuries," *Journal of Public Economics*, 2017, *156*, 200–213.

Pritchett, Lant, "The Future of Government: Basic Education and the (limited) role of technology in complex human endeavor," 2022. Published on Governance for Development.

Ramey, Garey and Valerie A Ramey, "The Rug Rat Race," *Brookings Papers on Economic Activity*, 2010, *2010* (1), 129–176.

Sun, Liyang and Sarah Abraham, "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, 2021, *225* (2), 175–199.

The Economist, "Technology is transforming what happens when a child goes to school," 2017.

UNICEF, "Growing Up in a Connected World Understanding Children's Risks and Opportunities in a Digital Age," *URL: https://www. unicef-irc. org/growing-up-connected*, 2019.

United Nations, "Digital Inclusion for a Sustainable Future: Summary of the Report of the UN Secretary-General's High-Level Panel on Digital Cooperation," 2019.

Vigdor, Jacob L, Helen F Ladd, and Erika Martinez, "Scaling the digital divide: Home computer technology and student achievement," *Economic inquiry*, 2014, *52* (3), 1103–1119.

A Main Tables and Figures

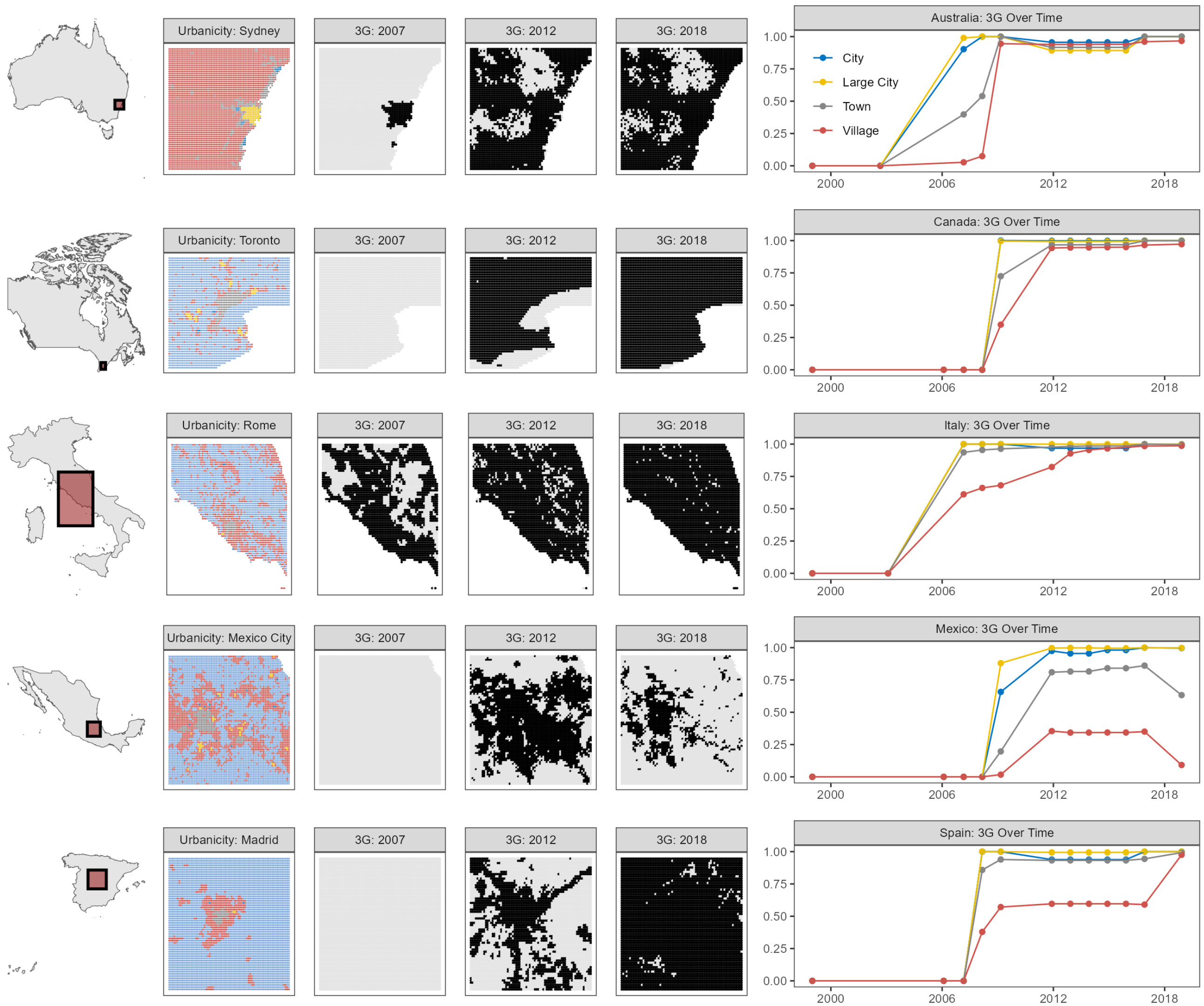


Figure A.1: 3G Calculation Illustration

Note: Figure summarizes the calculations for 3G expansion in five countries: Australia, Canada, Italy, Mexico, and Spain. For each country, maps display urbanicity and over-time 3G coverage for the largest urban area in the country.

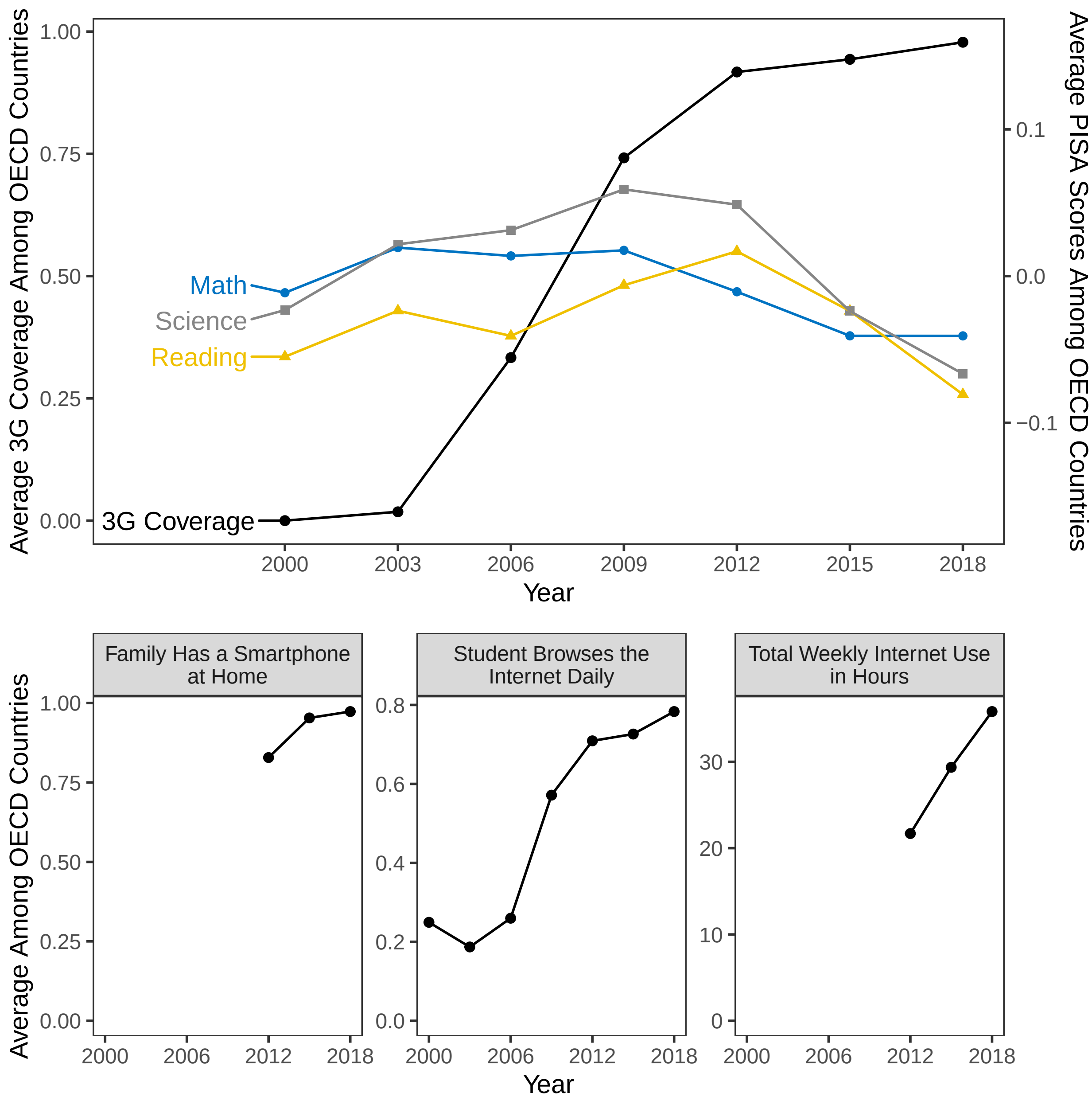
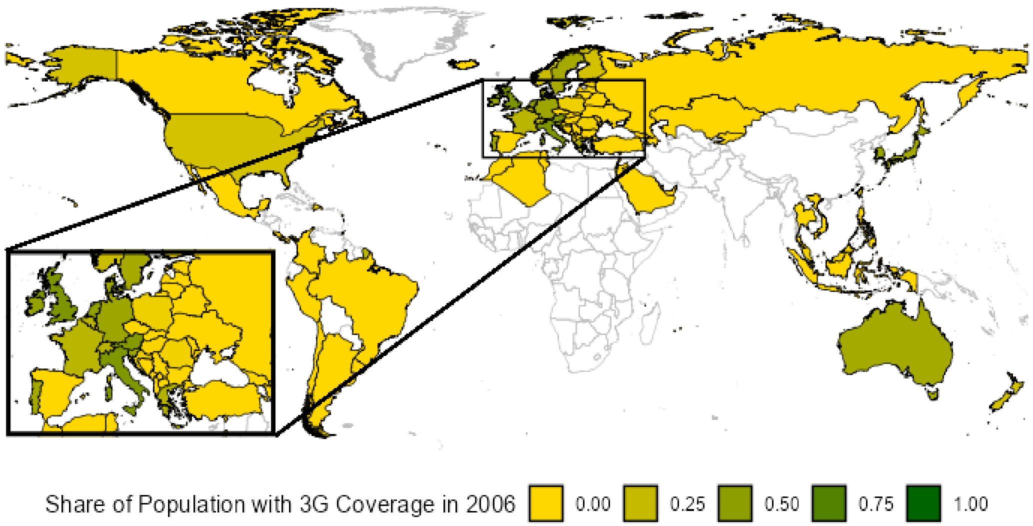


Figure A.2: Trends in 3G Coverage, Test scores, and Internet Access and Use in OECD Countries

Note: Figure displays trends in internet access and use in PISA countries. Sample countries are the OECD 23; the 23 countries with non-missing test scores in PISA exams from 2003 to 2022 and the set of countries used in most recent OECD PISA publications. Plotted points show averages of country-level values for each year in the sample.



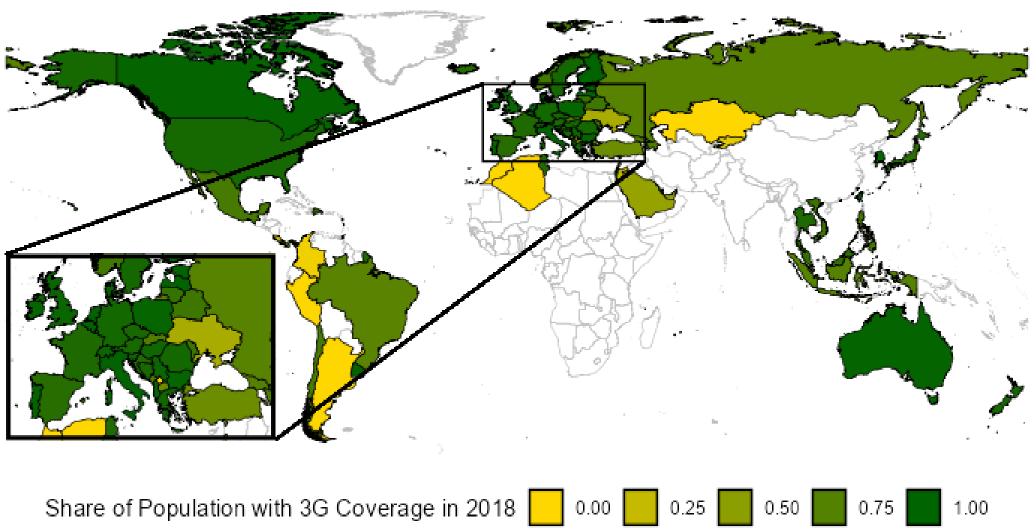


Figure A.3: Country-Level 3G Coverage in 2006 and 2018

Note: Figure displays the estimated country-level share of the population with 3G coverage in 2006 and 2018.

Table A.1: Summary Statistics

Statistic	N	Mean	St. Dev.
Panel A: Full Sample			
Male	2,600,134	0.496	0.500
Age	2,600,134	15.785	0.291
Is Immigrant	2,600,134	0.050	0.219
Father's Years of Education	2,600,134	13.059	4.138
Mother's Years of Education	2,600,134	13.022	4.251
School is Private, Independent	2,600,134	0.071	0.257
School is Private, Non-Independent	2,600,134	0.088	0.283
Weekly Homework Hours (2000-2006, 2012)	886,279	6.385	5.379
Days Skipped Past 2 Weeks (2012-2018)	1,251,516	0.827	1.476
Skipping Hinders Learning A Lot (2000-2003, 2009-2015)	2,192,073	0.076	0.265
Friendship Index (2000-2003, 2012-2018)	1,473,535	0.003	0.998
Belonging Index (2000-2003, 2012-2018)	1,482,513	−0.026	0.984
Self-Efficacy Index (2000-2006, 2012-2015)	1,340,914	−0.007	1.064
Math Score	2,600,134	−0.351	0.997
Reading Score	2,600,134	−0.362	1.018
Science Score	2,600,134	−0.309	0.992
Share of Population with 3G Coverage	2,600,134	0.575	0.424
Panel B: ICT Sample			
Male	1,595,699	0.494	0.500
Age	1,595,699	15.783	0.292
Is Immigrant	1,595,699	0.047	0.212
Father's Years of Education	1,595,699	13.281	3.883
Mother's Years of Education	1,595,699	13.327	3.942
School is Private, Independent	1,595,699	0.055	0.228
School is Private, Non-Independent	1,595,699	0.109	0.311
Weekly Homework Hours (2000-2006, 2012)	618,233	6.381	5.345
Days Skipped Past 2 Weeks (2012-2018)	790,297	0.749	1.395
Skipping Hinders Learning A Lot (2000-2003, 2009-2015)	1,327,988	0.070	0.255
Friendship Index (2000-2003, 2012-2018)	940,620	−0.010	0.989
Belonging Index (2000-2003, 2012-2018)	945,772	0.0001	1.002
Self-Efficacy Index (2000-2006, 2012-2015)	894,549	0.013	1.054
Math Score	1,595,699	−0.118	0.945
Reading Score	1,595,699	−0.135	0.950
Science Score	1,595,699	−0.086	0.942
Share of Population with 3G Coverage	1,595,699	0.614	0.421
Browses the Internet Daily	1,595,699	0.530	0.499
Has a Smartphone at Home (2012-2018)	838,077	0.899	0.301
Total Weekly Internet Use in Hours (2012-2018)	838,077	29.439	22.436

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 A.2: OLS Estimates: Effect of 3G on Technology Access and Use

	(1)	(2)
Panel A: Browses the Internet Daily		
3G	0.035+	0.039*
	(0.019)	(0.018)
Num.Obs.	1595699	1595699
R2	0.268	0.275
Panel B: Has a Smartphone at Home (2012-2018)		
3G	0.037	0.043
	(0.037)	(0.038)
Num.Obs.	838077	838077
R2	0.124	0.133
Panel C: Has a Smartphone at Home (2012-2018; 2000, 2003 Set to 0)		
3G	0.105*	0.104*
	(0.048)	(0.048)
Num.Obs.	1067892	1067892
R2	0.800	0.802
Panel D: Total Weekly Internet Use in Hours (2012-2018)		
3G	5.130**	4.882*
	(1.947)	(1.917)
Num.Obs.	838077	838077
R2	0.130	0.147
Country-by-Urbanicity FEs	✓	✓
Urbanicity-by-Year FEs	✓	✓
Country-by-Year FEs	✓	✓
Baseline Controls	✓	✓
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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ict} / \sum_{i \in ct} w_{ict}$, where w_{ict} is individual i in country c in year t's sampling weight, and $\sum_{i \in ct} w_{ict}$ denotes the sum of sampling weights in country c in year t. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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

	(1)	(2)
Panel A: Math		
3G	-0.076**	-0.073**
	(0.025)	(0.025)
Num.Obs.	2600134	2600134
R2	0.385	0.412
Panel B: Reading		
3G	-0.045+	-0.047*
	(0.024)	(0.024)
Num.Obs.	2600134	2600134
R2	0.361	0.388
Panel C: Science		
3G	-0.047*	-0.041+
	(0.024)	(0.023)
Num.Obs.	2600134	2600134
R2	0.342	0.372
Country-by-Urbanicity FEs	✓	✓
Urbanicity-by-Year FEs	✓	✓
Country-by-Year FEs	✓	✓
Baseline Controls	✓	✓
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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ict} / \sum_{i \in ct} w_{ict}$, where w_{ict} is individual i in country c in year t's sampling weight, and $\sum_{i \in ct} w_{ict}$ denotes the sum of sampling weights in country c in year t. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.4: OLS Estimates: Effect of 3G on Student Attitudes and Behaviors

	(1)	(2)
Panel A: Friendship Index (2000-2003, 2012-2018)		
3G	-0.145***	-0.152***
	(0.028)	(0.030)
Num.Obs.	1473535	1473535
R2	0.041	0.048
Panel B: Belonging Index (2000-2003, 2012-2018)		
3G	-0.067*	-0.089*
	(0.034)	(0.035)
Num.Obs.	1482513	1482513
R2	0.055	0.064
Panel C: Self-Efficacy Index (2000-2006, 2012-2015)		
3G	-0.056	-0.048
	(0.036)	(0.037)
Num.Obs.	1340914	1340914
R2	0.071	0.084
Panel D: Weekly Homework Hours (2000-2006, 2012)		
3G	0.300+	0.365+
	(0.178)	(0.195)
Num.Obs.	886279	886279
R2	0.161	0.177
Panel E: Days Skipped Past 2 Weeks (2012-2018)		
3G	0.014	0.026
	(0.084)	(0.081)
Num.Obs.	1251516	1251516
R2	0.127	0.139
Panel F: Skipping Hinders Learning A Lot (2000-2003, 2009-2015)		
3G	0.026	0.027
	(0.018)	(0.018)
Num.Obs.	2192073	2192073
R2	0.110	0.127
Country-by-Urbanicity FEs	✓	✓
Urbanicity-by-Year FEs	✓	✓
Country-by-Year FEs	✓	✓
Baseline Controls	✓	✓
Controls Interacted with Country-by-Urbanicity		✓

Note: Table displays OLS results estimating the effect of 3G coverage on student attitudes and behaviors. Dependent variables in Panels A, B, and C 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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ict} / \sum_{i \in ct} w_{ict}$, where w_{ict} is individual i in country c in year t's sampling weight, and $\sum_{i \in ct} w_{ict}$ denotes the sum of sampling weights in country c in year t. These variables are not available for all countries in all years; see Appendix Figures F.6, F.7, F.8, F.3 F.4 and F.5. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B 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.

B.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.

B.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.[19]

B.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™>).

[19] We note that the number of reported plausible values varies from year to year. Prior to 2015, 5 plausible values were reported. In 2015 and later, 10 plausible values were reported. We average across all available plausible values.

- **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.

B.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.

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

B.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 recode 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.

B.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.

In all rounds except 2006, the school administrators were also asked "In your school, to what extent is the learning of students hindered by the following phenomena? — Students Skipping Classes. The responses were: 'Not at all', 'A little', 'To some extent', and 'A lot'. We report the effect of 3G arrival on their likelihood of reporting that skipping classes hinders learning (a) 'A lot' and (b) 'To some extent', or 'A lot'.

B.7 Social Connectedness and Well-being 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.

C 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 two thresholds of treatment, which 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, we include estimates using this “balanced sample" in the difference-in-differences tables below.

We perform these analyses on data collapsed at the country-by-urbanicity-by-year level to simplify computation. Specifically, we first regress all outcomes (measures of internet use and test scores) on our set of baseline covariates and capture the residuals of this regression. We refer to these as "demographic-adjusted outcomes." Next, we compute average demographic-adjusted outcomes at the country-by-urbanicity-by-year level, weighted by PISA sampling weights. These average demographic-adjusted outcomes are our dependent variables in all analyses in this Appendix. Across all analyses, we weight each observation by w_{cut}/w_{ct}, where w_{cut} is the sum of sampling weights in country c and urbanicity u and year t, and w_{ct} denotes the sum of sampling weights in country c and year t.

In our analysis, including urbanicity-by-year fixed effects in the full unbalanced panel results in matrix singularity, making it infeasible to compute standard errors. We, therefore, present estimates where we have excluded these fixed effects from our two-stage difference-in-differences models. The flat pre-trends in our event studies, described below, suggest that our parallel trends assumption is reasonable. This approach ensures technical feasibility while preserving the integrity of our findings. We also note that all of our main results using the main difference-in-differences estimator are also robust to the exclusion of urbanicity-by-year FE. If we restrict the data only to the balanced panel, we also note that our estimates from the two-stage difference-in-differences models estimator with urbanicity by year FEs are similar sized but slightly less precise. These results are available upon request

Appendix Table C.1 summarizes our results with respect to technology access and use. Only two of the four variables included in Table A.2 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. All estimates use the ICT sample, identical to the sample used in our main estimates in Table A.2. Column 1 contains OLS estimates; Columns 2 and 3 contain the two-stage difference-in-difference estimates with varying thresholds of 3G coverage used to identify treated versus untreated units.

Estimates in Panel A of Table C.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 nearly identical to OLS estimates. Similarly, 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 C.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 3) as well as the balanced sample (shown in Columns 4 through 6). Generally, estimates using two-stage differences-in-differences are slightly larger in magnitude than estimates using OLS.

Figure C.1 shows our event study results with respect to 3G coverage (in Panel A) and test scores (in Panel B). Both estimates are performed on the balanced sample, described above. 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 a lower 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. 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.

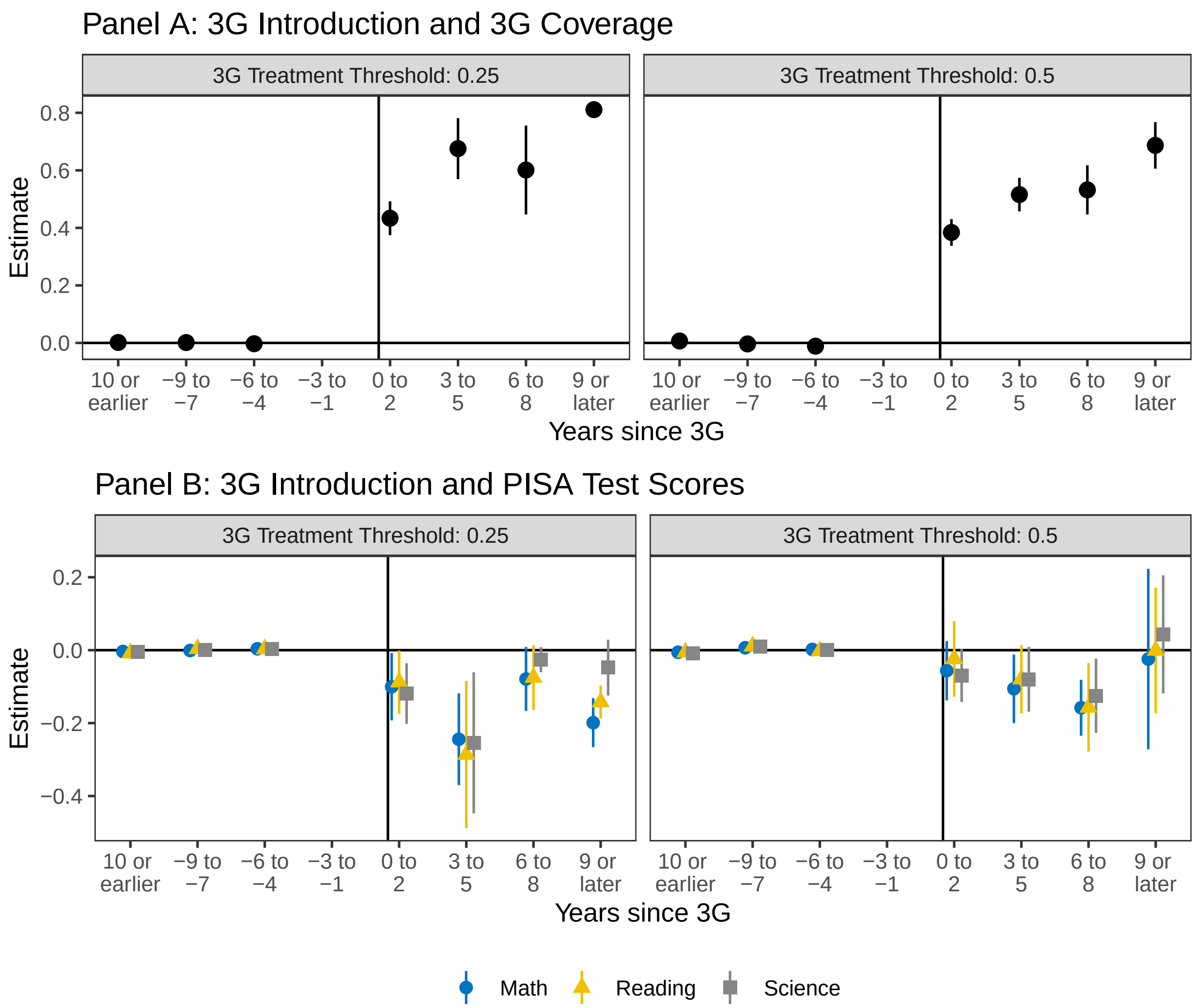


Figure C.1: Effect of 3G Entry on PISA Test Scores: Two-Stage Difference-in-Differences

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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Analyses are performed on data collapsed at the country-by-urbanicity-by-year level. Observations are weighted by w_{cut}/w_{ct}, where w_{cut} is the sum of sampling weights in country c and urbanicity u and year t, and w_{ct} denotes the sum of sampling weights in country c and year t. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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

	ICT Sample		
Method:	OLS	2SDiD	
	(1)	(2)	(3)
Panel A: Browses the Internet Daily			
3G	0.073**	0.094***	0.078***
	(0.024)	(0.018)	(0.017)
Num.Obs.	1003	501	595
R2	0.993	0.217	0.178
Panel B: Has a Smartphone at Home (2012-2018; 2000, 2003 Set to 0)			
3G	0.115*	0.090***	0.060*
	(0.055)	(0.022)	(0.029)
Num.Obs.	716	312	361
R2	0.999	0.328	0.136
3G Treatment Threshold	-	0.25	0.5
Country-by-Urbanicity FEs	✓	✓	✓
Country-by-Year FEs	✓	✓	✓
Residualized on 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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Analyses are performed on data collapsed at the country-by-urbanicity-by-year level. Observations are weighted by w_{cut}/w_{ct}, where w_{cut} is the sum of sampling weights in country c and urbanicity u and year t, and w_{ct} denotes the sum of sampling weights in country c and year t. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table C.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)
Panel A: Math						
3G	-0.077**	-0.200***	-0.073**	-0.096**	-0.204***	-0.099**
	(0.029)	(0.046)	(0.026)	(0.036)	(0.056)	(0.036)
Num.Obs.	1408	720	854	794	404	482
R2	0.989	0.113	0.045	0.976	0.132	0.066
Panel B: Reading						
3G	-0.034	-0.184***	-0.063*	-0.050	-0.193**	-0.066+
	(0.028)	(0.052)	(0.031)	(0.034)	(0.065)	(0.040)
Num.Obs.	1408	720	854	794	404	482
R2	0.986	0.091	0.023	0.967	0.109	0.021
Panel C: Science						
3G	-0.066*	-0.198***	-0.080**	-0.091**	-0.196**	-0.091**
	(0.027)	(0.053)	(0.025)	(0.033)	(0.064)	(0.032)
Num.Obs.	1408	720	854	794	404	482
R2	0.988	0.111	0.058	0.973	0.126	0.064
3G Treatment Threshold	-	0.25	0.5	-	0.25	0.5
Country-by-Urbanicity FEs	✓	✓	✓	✓	✓	✓
Country-by-Year FEs	✓	✓	✓	✓	✓	✓
Residualized on 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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Analyses are performed on data collapsed at the country-by-urbanicity-by-year level. Balanced Sample limits our sample to the set of country-by-urbanicity pairs that appear in all 6 PISA rounds between 2003 and 2018. Observations are weighted by w_{cut}/w_{ct}, where w_{cut} is the sum of sampling weights in country c and urbanicity u and year t, and w_{ct} denotes the sum of sampling weights in country c and year t. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

D Instrumental Variables Estimates

As discussed briefly in the main text, 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.

Following the literature, 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.

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

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.

In Appendix Table D.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.

Next, we describe results using instrumental variables to estimate the effects of 3G on student test scores. Table D.2 shows instrumental variables estimates of the effect of 3G on test scores in math, and science. Column 1 of Table D.2 displays OLS estimates of the effect of 3G on test scores. These results are identical to those displayed in Column 1 of Table A.3, and suggest small and negative effects on student test scores.

Column 2 of Table D.2 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 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 D.2 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 D.2 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 A.3; 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 D.3 and D.4 display results that repeat this analysis using only the lightning and 2G instruments, respectively, with qualitatively similar results.

Table D.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	-0.006***	0.000	
	(0.002)	(0.001)	
2G × Year	0.005+	0.011***	
	(0.003)	(0.002)	
$\hat{3G}$			0.195
			(0.162)
F-Stat			7.71
Num.Obs.	1595699	1595699	1595699
R2	0.878	0.246	0.244
Panel B: Has a Smartphone at Home (2012-2018)			
Lightning × Year	0.021+	0.002	
	(0.012)	(0.002)	
2G × Year	0.012*	0.017***	
	(0.005)	(0.002)	
$\hat{3G}$			0.132*
			(0.054)
F-Stat			2.84
Num.Obs.	838077	838077	838077
R2	0.883	0.114	0.112
Panel C: Has a Smartphone at Home (2012-2018; 2000, 2003 Set to 0)			
Lightning × Year	-0.005***	-0.002**	
	(0.001)	(0.001)	
2G × Year	0.006**	0.000	
	(0.002)	(0.001)	
$\hat{3G}$			0.288*
			(0.114)
F-Stat			12.38
Num.Obs.	1067892	1067892	1067892
R2	0.950	0.795	0.793
Panel D: Total Weekly Internet Use in Hours (2012-2018)			
Lightning × Year	0.021+	0.043	
	(0.012)	(0.098)	
2G × Year	0.012*	0.341	
	(0.005)	(0.269)	
$\hat{3G}$			3.046
			(4.511)
F-Stat			2.84
Num.Obs.	838077	838077	838077
R2	0.883	0.124	0.124
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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ict} / \sum_{i \in ct} w_{ict}$, where w_{ict} is individual i in country c in year t's sampling weight, and $\sum_{i \in ct} w_{ict}$ denotes the sum of sampling weights in country c in year t. + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001.

Table D.2: 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	-0.034			
	(0.034)			
Lightning × Year		-0.008***	0.005***	
		(0.002)	(0.001)	
2G × Year		0.005	0.009	
		(0.004)	(0.006)	
$\widehat{3G}$				-0.550*
				(0.224)
F-Stat				12.50
Num.Obs.	2600134	2600134	2600134	2600134
R2	0.370	0.850	0.371	0.363
Panel B: Reading				
3G	-0.046			
	(0.034)			
Lightning × Year		-0.008***	0.003*	
		(0.002)	(0.001)	
2G × Year		0.005	0.006	
		(0.004)	(0.006)	
$\widehat{3G}$				-0.325+
				(0.192)
F-Stat				12.50
Num.Obs.	2600134	2600134	2600134	2600134
R2	0.345	0.850	0.345	0.343
Panel C: Science				
3G	-0.005			
	(0.030)			
Lightning × Year		-0.008***	0.004**	
		(0.002)	(0.001)	
2G × Year		0.005	0.012*	
		(0.004)	(0.005)	
$\widehat{3G}$				-0.329*
				(0.162)
F-Stat				12.50
Num.Obs.	2600134	2600134	2600134	2600134
R2	0.329	0.850	0.329	0.326
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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ict} / \sum_{i \in ct} w_{ict}$, where w_{ict} is individual i in country c in year t's sampling weight, and $\sum_{i \in ct} w_{ict}$ denotes the sum of sampling weights in country c in year t. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table D.3: 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	-0.034			
	(0.034)			
Lightning × Year		-0.008***	0.005***	
		(0.002)	(0.001)	
$\hat{3G}$				-0.638*
				(0.250)
F-Stat				22.23
Num.Obs.	2600134	2600134	2600134	2600134
R2	0.370	0.850	0.371	0.360
Panel B: Reading				
3G	-0.046			
	(0.034)			
Lightning × Year		-0.008***	0.003*	
		(0.002)	(0.001)	
$\hat{3G}$				-0.380+
				(0.208)
F-Stat				22.23
Num.Obs.	2600134	2600134	2600134	2600134
R2	0.345	0.850	0.345	0.342
Panel C: Science				
3G	-0.005			
	(0.030)			
Lightning × Year		-0.008***	0.003**	
		(0.002)	(0.001)	
$\hat{3G}$				-0.430*
				(0.184)
F-Stat				22.23
Num.Obs.	2600134	2600134	2600134	2600134
R2	0.329	0.850	0.329	0.323
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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ict} / \sum_{i \in ct} w_{ict}$, where w_{ict} is individual i in country c in year t's sampling weight, and $\sum_{i \in ct} w_{ict}$ denotes the sum of sampling weights in country c in year t. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table D.4: 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	-0.034			
	(0.034)			
2G × Year		0.007	0.008	
		(0.005)	(0.006)	
$\hat{3G}$				1.060
				(1.105)
F-Stat				2.53
Num.Obs.	2600134	2600134	2600134	2600134
R2	0.370	0.844	0.371	0.336
Panel B: Reading				
3G	-0.046			
	(0.034)			
2G × Year		0.007	0.005	
		(0.005)	(0.006)	
$\hat{3G}$				0.676
				(0.902)
F-Stat				2.53
Num.Obs.	2600134	2600134	2600134	2600134
R2	0.345	0.844	0.345	0.331
Panel C: Science				
3G	-0.005			
	(0.030)			
2G × Year		0.007	0.011*	
		(0.005)	(0.005)	
$\hat{3G}$				1.519
				(1.255)
F-Stat				2.53
Num.Obs.	2600134	2600134	2600134	2600134
R2	0.329	0.844	0.329	0.261
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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ict} / \sum_{i \in ct} w_{ict}$, where w_{ict} is individual i in country c in year t's sampling weight, and $\sum_{i \in ct} w_{ict}$ denotes the sum of sampling weights in country c in year t. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

E Additional Figures and Tables

Table E.1: Associations Between Digital Technology Use and PISA Test Scores

	(1)	(2)	(3)	(4)
Panel A: Math				
Total Weekly Internet Use in Hours	-0.005***			-0.006***
	(0.000)			(0.000)
Has a Smartphone at Home		0.028*		0.036***
		(0.011)		(0.010)
Browses Internet Daily			0.154***	0.211***
			(0.013)	(0.012)
Num.Obs.	838077	838077	838077	838077
R2	0.334	0.324	0.329	0.343
Panel B: Reading				
Total Weekly Internet Use in Hours	-0.004***			-0.005***
	(0.000)			(0.000)
Has a Smartphone at Home		0.046***		0.041***
		(0.012)		(0.010)
Browses Internet Daily			0.231***	0.285***
			(0.014)	(0.013)
Num.Obs.	838077	838077	838077	838077
R2	0.284	0.277	0.288	0.301
Panel C: Science				
Total Weekly Internet Use in Hours	-0.004***			-0.006***
	(0.000)			(0.000)
Has a Smartphone at Home		0.016		0.019+
		(0.011)		(0.010)
Browses Internet Daily			0.191***	0.249***
			(0.013)	(0.012)
Num.Obs.	838077	838077	838077	838077
R2	0.293	0.284	0.292	0.306
Country-by-Urbanicity FEs	✓	✓	✓	✓
Urbanicity-by-Year FEs	✓	✓	✓	✓
Country-by-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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ict} / \sum_{i \in ct} w_{ict}$, where w_{ict} is individual i in country c in year t's sampling weight, and $\sum_{i \in ct} w_{ict}$ denotes the sum of sampling weights in country c in year t. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.2: OLS Estimates: Effect of 3G on Reported Weekly Internet Use

	(1)	(2)
Panel A: In-School Weekly Internet Use in Hours (2012-2018)		
3G	0.999	0.870
	(0.758)	(0.792)
Num.Obs.	838077	838077
R2	0.095	0.107
Panel B: Out-of-School Weekly Internet Use in Hours (2012-2018)		
3G	4.130**	4.012**
	(1.523)	(1.461)
Num.Obs.	838077	838077
R2	0.113	0.133
Panel C: Total Weekly Internet Use in Hours (2012-2018)		
3G	5.130**	4.882*
	(1.947)	(1.917)
Num.Obs.	838077	838077
R2	0.130	0.147
Country-by-Urbanicity FEs	✓	✓
Urbanicity-by-Year FEs	✓	✓
Country-by-Year FEs	✓	✓
Baseline Controls	✓	✓
Controls Interacted with Country-by-Urbanicity		✓

Note: Table displays OLS results estimating the effect of 3G coverage on reported weekly internet 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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ict} / \sum_{i \in ct} w_{ict}$, where w_{ict} is individual i in country c in year t's sampling weight, and $\sum_{i \in ct} w_{ict}$ denotes the sum of sampling weights in country c in year t. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.3: OLS Estimates: Effect of 3G on PISA Test Scores (ICT Sample)

	(1)	(2)
Panel A: Math		
3G	-0.101**	-0.083**
	(0.031)	(0.030)
Num.Obs.	1595699	1595699
R2	0.333	0.358
Panel B: Reading		
3G	-0.056+	-0.039
	(0.033)	(0.031)
Num.Obs.	1595699	1595699
R2	0.301	0.326
Panel C: Science		
3G	-0.071*	-0.052+
	(0.031)	(0.030)
Num.Obs.	1595699	1595699
R2	0.283	0.309
Country-by-Urbanicity FEs	✓	✓
Urbanicity-by-Year FEs	✓	✓
Country-by-Year FEs	✓	✓
Baseline Controls	✓	✓
Controls Interacted with Country-by-Urbanicity		✓

Note: Table displays OLS results estimating the effect of 3G coverage on test scores within the ICT Sample. 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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ict} / \sum_{i \in ct} w_{ict}$, where w_{ict} is individual i in country c in year t's sampling weight, and $\sum_{i \in ct} w_{ict}$ denotes the sum of sampling weights in country c in year t. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.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)		Total Weekly Internet Use in Hours (2012-2018)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: By Student Gender								
3G	0.031	0.030	0.056	0.056	0.099*	0.099*	5.584**	5.711**
	(0.020)	(0.020)	(0.034)	(0.035)	(0.045)	(0.046)	(2.063)	(2.099)
3G × Female	0.009	0.014	-0.036	-0.024	0.014	0.014	-0.704	-1.551
	(0.019)	(0.018)	(0.035)	(0.036)	(0.018)	(0.019)	(2.186)	(2.196)
Num.Obs.	1595699	1595699	838077	838077	1067892	1067892	838077	838077
R2	0.271	0.273	0.125	0.129	0.800	0.801	0.134	0.143
Panel B: By Parental Education								
3G	0.073**	0.072**	0.056+	0.054	0.126*	0.128*	5.276*	5.274*
	(0.024)	(0.024)	(0.033)	(0.034)	(0.053)	(0.053)	(2.249)	(2.301)
3G × Either Parent has Tert. Ed.	-0.074**	-0.070**	-0.046	-0.043	-0.089*	-0.097*	-2.039	-2.226
	(0.024)	(0.026)	(0.039)	(0.038)	(0.043)	(0.045)	(2.466)	(2.494)
Num.Obs.	1595699	1595699	838077	838077	1067892	1067892	838077	838077
R2	0.271	0.274	0.127	0.129	0.801	0.801	0.136	0.143
Panel C: By Country Income Level								
3G	0.052*	0.053*	0.054	0.051	0.097+	0.099+	6.256**	6.168**
	(0.020)	(0.021)	(0.039)	(0.043)	(0.050)	(0.051)	(2.153)	(2.197)
3G × Country is High Income in 2000	-0.114***	-0.095**	-0.099+	-0.106	-0.113*	-0.104+	-5.451	-3.790
	(0.029)	(0.030)	(0.056)	(0.065)	(0.053)	(0.056)	(5.903)	(5.927)
Num.Obs.	1595699	1595699	838077	838077	1067892	1067892	838077	838077
R2	0.270	0.267	0.125	0.122	0.800	0.800	0.134	0.138
Country-by-Urbanicity FEs	✓	✓	✓	✓	✓	✓	✓	✓
Urbanicity-by-Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Country-by-Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓
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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. 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 $w_{ict} / \sum_{i \in ct} w_{ict}$, where w_{ict} is individual i in country c in year t's sampling weight, and $\sum_{i \in ct} w_{ict}$ denotes the sum of sampling weights in country c in year t. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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

	Math		Reading		Science	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: By Student Gender						
3G	-0.062*	-0.082*	-0.027	-0.049	-0.021	-0.042
	(0.029)	(0.033)	(0.028)	(0.032)	(0.027)	(0.031)
3G × Female	-0.031	-0.008	-0.042	-0.012	-0.053*	-0.021
	(0.026)	(0.031)	(0.026)	(0.031)	(0.026)	(0.031)
Num.Obs.	2600134	2600134	2600134	2600134	2600134	2600134
R2	0.388	0.372	0.365	0.347	0.346	0.328
Panel B: By Parental Education						
3G	-0.076**	-0.079*	-0.054*	-0.064*	-0.059*	-0.064*
	(0.029)	(0.031)	(0.027)	(0.030)	(0.027)	(0.029)
3G × Either Parent has Tert. Ed.	0.016	0.028	0.032	0.052	0.039	0.060*
	(0.031)	(0.031)	(0.034)	(0.034)	(0.029)	(0.030)
Num.Obs.	2600134	2600134	2600134	2600134	2600134	2600134
R2	0.394	0.390	0.369	0.349	0.351	0.348
Panel C: By Country Income Level						
3G	-0.055	-0.063+	-0.043	-0.056	-0.058+	-0.067+
	(0.034)	(0.038)	(0.033)	(0.039)	(0.032)	(0.037)
3G × Country is High Income in 2000	0.025	0.050	0.062	0.082	0.085	0.120*
	(0.056)	(0.060)	(0.056)	(0.061)	(0.055)	(0.059)
Num.Obs.	2600134	2600134	2600134	2600134	2600134	2600134
R2	0.386	0.378	0.362	0.339	0.344	0.338
Country-by-Urbanicity FEs	✓	✓	✓	✓	✓	✓
Urbanicity-by-Year FEs	✓	✓	✓	✓	✓	✓
Country-by-Year FEs	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓
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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. 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 $w_{ict} / \sum_{i \in ct} w_{ict}$, where w_{ict} is individual i in country c in year t's sampling weight, and $\sum_{i \in ct} w_{ict}$ denotes the sum of sampling weights in country c in year t. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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

	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)
Panel A: By Student Gender						
3G	-0.120**	-0.120**	-0.082*	-0.086*	-0.085*	-0.104*
	(0.039)	(0.040)	(0.036)	(0.039)	(0.041)	(0.044)
3G × Female	-0.053	-0.053	0.019	0.017	0.061	0.085+
	(0.056)	(0.056)	(0.045)	(0.047)	(0.043)	(0.048)
Num.Obs.	1473535	1473535	1482513	1482513	1340914	1340914
R2	0.044	0.047	0.059	0.061	0.078	0.073
Panel B: By Parental Education						
3G	-0.111**	-0.109**	-0.012	-0.010	-0.045	-0.044
	(0.036)	(0.037)	(0.040)	(0.041)	(0.040)	(0.042)
3G × Either Parent has Tert. Ed.	-0.061	-0.094	-0.094	-0.122+	-0.011	0.000
	(0.057)	(0.059)	(0.063)	(0.068)	(0.040)	(0.048)
Num.Obs.	1473535	1473535	1482513	1482513	1340914	1340914
R2	0.042	0.047	0.057	0.061	0.076	0.077
Panel C: By Country Income Level						
3G	-0.124***	-0.122***	-0.053	-0.051	-0.080	-0.079
	(0.035)	(0.036)	(0.041)	(0.043)	(0.050)	(0.053)
3G × Country is High Income in 2000	0.065	0.096+	0.063	0.057	0.135+	0.116
	(0.062)	(0.057)	(0.070)	(0.069)	(0.071)	(0.078)
Num.Obs.	1473535	1473535	1482513	1482513	1340914	1340914
R2	0.041	0.044	0.056	0.057	0.074	0.072
Country-by-Urbanicity FEs	✓	✓	✓	✓	✓	✓
Urbanicity-by-Year FEs	✓	✓	✓	✓	✓	✓
Country-by-Year FEs	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓
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 and mental well-being. 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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. 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 $w_{ict} / \sum_{i \in ct} w_{ict}$, where w_{ict} is individual i in country c in year t's sampling weight, and $\sum_{i \in ct} w_{ict}$ denotes the sum of sampling weights in country c in year t. These variables are not available for all countries in all years; see Appendix Figures F.6, F.7, and F.8. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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

	Weekly Homework Hours (2000-2006, 2012)		Days Skipped Past 2 Weeks (2012-2018)		Skipping Hinders Learning A Lot (2000-2003, 2009-2015)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: By Student Gender						
3G	0.180	0.140	-0.031	-0.023	0.017	0.019
	(0.195)	(0.197)	(0.082)	(0.083)	(0.022)	(0.021)
3G × Female	0.241	0.408+	0.086	0.044	0.018	0.020
	(0.212)	(0.232)	(0.112)	(0.109)	(0.013)	(0.014)
Num.Obs.	886279	886279	1251516	1251516	2192073	2192073
R2	0.167	0.173	0.131	0.135	0.112	0.119
Panel B: By Parental Education						
3G	0.163	0.245	-0.120	-0.123	0.025	0.025
	(0.226)	(0.176)	(0.076)	(0.076)	(0.021)	(0.021)
3G × Either Parent has Tert. Ed.	0.102	0.000	0.224*	0.208*	0.002	0.004
	(0.293)	(0.000)	(0.101)	(0.104)	(0.021)	(0.020)
Num.Obs.	886279	886279	1251516	1251516	2192073	2192073
R2	0.164	0.164	0.129	0.134	0.113	0.121
Panel C: By Country Income Level						
3G	0.105	0.174	-0.073	-0.069	0.031	0.032
	(0.278)	(0.292)	(0.076)	(0.075)	(0.020)	(0.019)
3G × Country is High Income in 2000	0.175	0.057	0.327	0.307	-0.042	-0.047
	(0.374)	(0.398)	(0.199)	(0.207)	(0.038)	(0.037)
Num.Obs.	886279	886279	1251516	1251516	2192073	2192073
R2	0.162	0.160	0.128	0.129	0.110	0.113
Country-by-Urbanicity FEs	✓	✓	✓	✓	✓	✓
Urbanicity-by-Year FEs	✓	✓	✓	✓	✓	✓
Country-by-Year FEs	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓
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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. 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 $w_{ict} / \sum_{i \in ct} w_{ict}$, where w_{ict} is individual i in country c in year t's sampling weight, and $\sum_{i \in ct} w_{ict}$ denotes the sum of sampling weights in country c in year t. These variables are not available for all countries in all years; see Appendix Figures F.3, F.4 and F.5. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.8: Heterogeneous Effects of 3G on Reported Weekly Internet Use

	In-School Weekly Internet Use in Hours (2012-2018)		Out-of-School Weekly Internet Use in Hours (2012-2018)		Total Weekly Internet Use in Hours (2012-2018)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: By Student Gender						
3G	0.671	0.694	4.913**	5.018**	5.584**	5.711**
	(0.845)	(0.845)	(1.750)	(1.785)	(2.063)	(2.099)
3G × Female	0.808	0.512	-1.513	-2.062	-0.704	-1.551
	(0.936)	(0.903)	(1.690)	(1.774)	(2.186)	(2.196)
Num.Obs.	838077	838077	838077	838077	838077	838077
R2	0.097	0.104	0.118	0.128	0.134	0.143
Panel B: By Parental Education						
3G	0.426	0.432	4.850**	4.842**	5.276*	5.274*
	(0.940)	(0.945)	(1.667)	(1.715)	(2.249)	(2.301)
3G × Either Parent has Tert. Ed.	0.571	0.543	-2.610	-2.769+	-2.039	-2.226
	(1.302)	(1.310)	(1.582)	(1.584)	(2.466)	(2.494)
Num.Obs.	838077	838077	838077	838077	838077	838077
R2	0.098	0.105	0.120	0.128	0.136	0.143
Panel C: By Country Income Level						
3G	0.950	0.973	5.306**	5.196**	6.256**	6.168**
	(0.841)	(0.842)	(1.688)	(1.758)	(2.153)	(2.197)
3G × Country is High Income in 2000	0.393	0.776	-5.844	-4.566	-5.451	-3.790
	(2.192)	(2.177)	(4.942)	(5.045)	(5.903)	(5.927)
Num.Obs.	838077	838077	838077	838077	838077	838077
R2	0.096	0.102	0.119	0.122	0.134	0.138
Country-by-Urbanicity FEs	✓	✓	✓	✓	✓	✓
Urbanicity-by-Year FEs	✓	✓	✓	✓	✓	✓
Country-by-Year FEs	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓
Controls Interacted with Country-by-Urbanicity		✓		✓		✓
Complete Interactions with Heterogeneous Variable	✓	✓	✓	✓	✓	✓

Note: Table displays OLS results estimating the heterogeneous effect of 3G coverage on reported weekly internet 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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. 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 $w_{ict} / \sum_{i \in ct} w_{ict}$, where w_{ict} is individual i in country c in year t's sampling weight, and $\sum_{i \in ct} w_{ict}$ denotes the sum of sampling weights in country c in year t. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.9: OLS Estimates: Effect of 3G on School Administrator's Perceived Skipping Burden

	(1)	(2)
Panel A: Skipping Hinders Learning A Lot (2000-2003, 2009-2015)		
3G	0.026	0.027
	(0.018)	(0.018)
Num.Obs.	2192073	2192073
R2	0.110	0.127
Panel B: Skipping Hinders Learning Some or A Lot (2000-2003, 2009-2015)		
3G	0.049	0.047
	(0.030)	(0.031)
Num.Obs.	2192073	2192073
R2	0.169	0.195
Country-by-Urbanicity FEs	✓	✓
Urbanicity-by-Year FEs	✓	✓
Country-by-Year FEs	✓	✓
Baseline Controls	✓	✓
Controls Interacted with Country-by-Urbanicity		✓

Note: Table displays OLS results estimating the effect of 3G coverage on the school administrator's perceived burden of student absenteeism. School administrators were asked each year whether "In your school, to what extent is the learning of students hindered by the following phenomena? — Students Skipping Classes. The responses were: 'Not at all', 'A little', 'To some extent', and 'A lot'. Panel A reports the regression of the responses 'A lot' and Panel B reports the results combining the responses 'To some extent' and 'A lot'. 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 dummy variables identifying students with missing father's education, missing mother's education, missing immigration status, and missing school type. Robust standard errors clustered at the country-by-urbanicity level in parentheses. Observations are weighted by $w_{ict} / \sum_{i \in ct} w_{ict}$, where w_{ict} is individual i in country c in year t's sampling weight, and $\sum_{i \in ct} w_{ict}$ denotes the sum of sampling weights in country c in year t. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E.10: Calculation of 3G-Induced Decline in Test Scores due to Absenteeism

	Parameter	**Value**
A	Instruction Hours Per Year (OECD, 2023)	923
B	Number of Instruction Days Per Year (OECD, 2023)	184
C	Instruction Hours Per Day (A/B)	5.02
D	Estimated 3G Effect on Days Skipped in Two Weeks (Table A.4)	0.02
E	Hours of Instruction Missed Per Week (C*D)	0.05
F	Effect of 1 Hour of Instruction on Test Scores (Lavy, 2015)	0.06
G	Effect of 3G-Induced Instruction Missed (-E*F)	-0.003

Note: Table displays calculations that estimate the impact of 3G-induced missed instruction on test scores.

F Data Availability

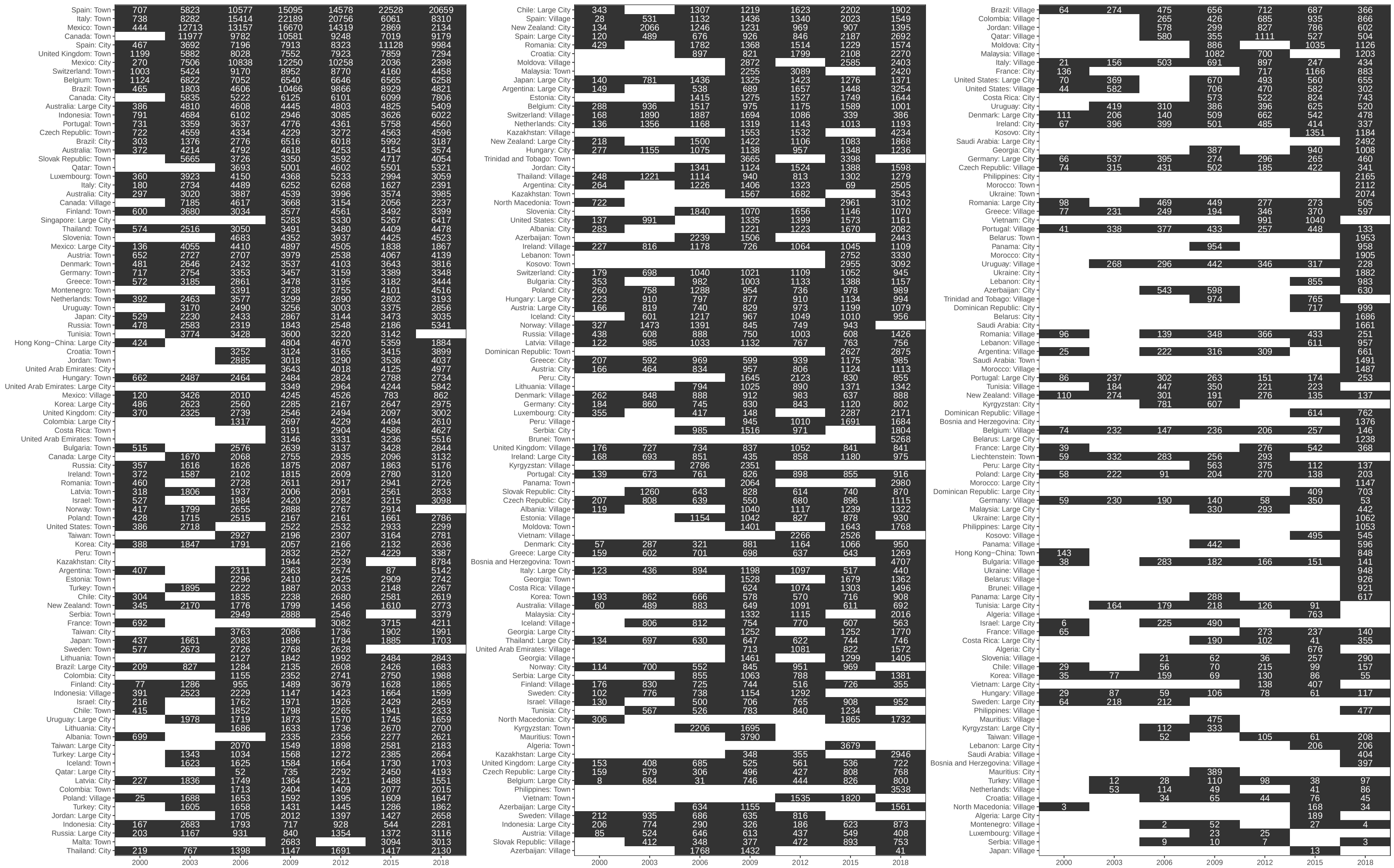


Figure F.1: Data Coverage by Country and Year

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

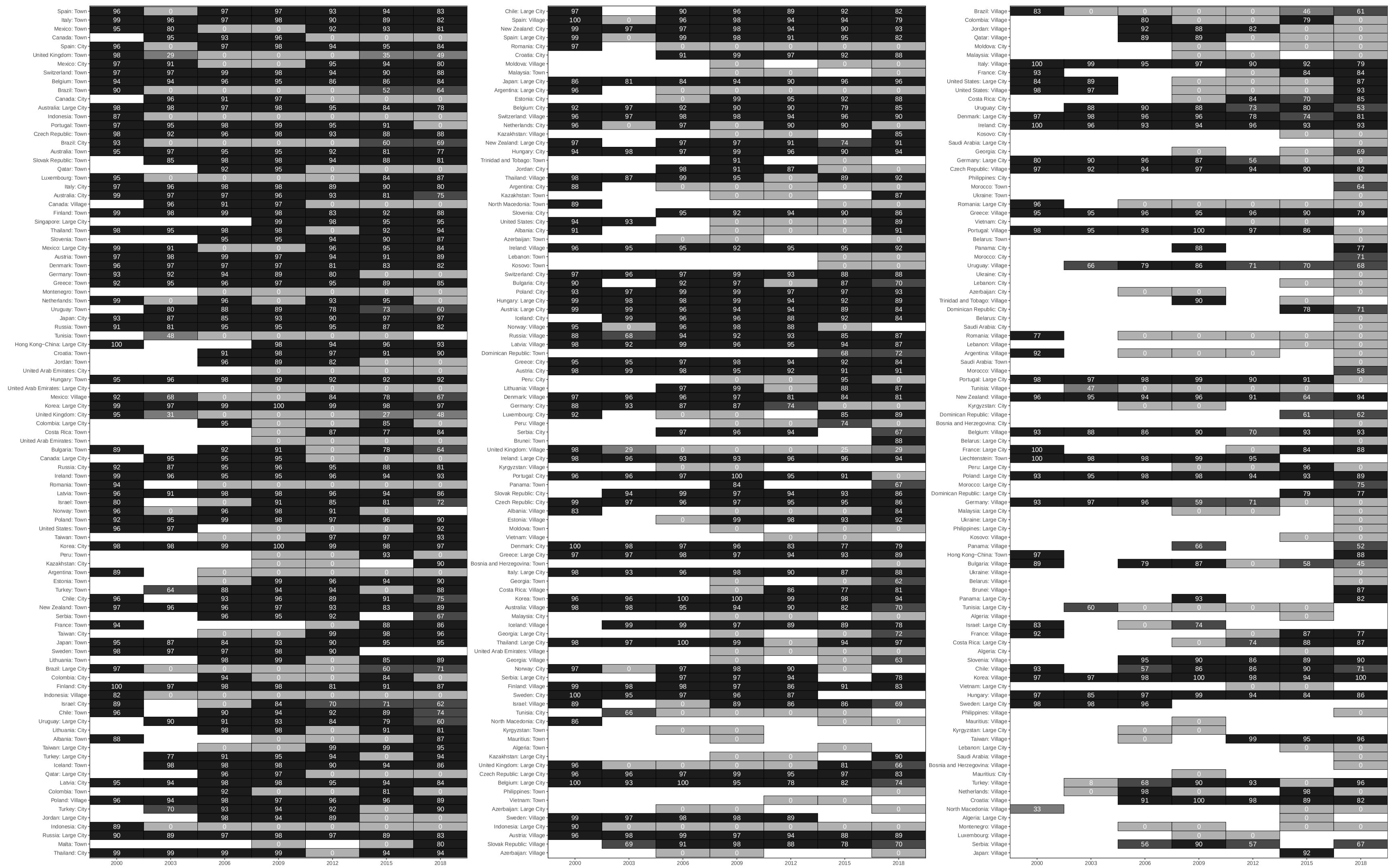


Figure F.2: ICT Sample: Data Availability by Country and Year

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.

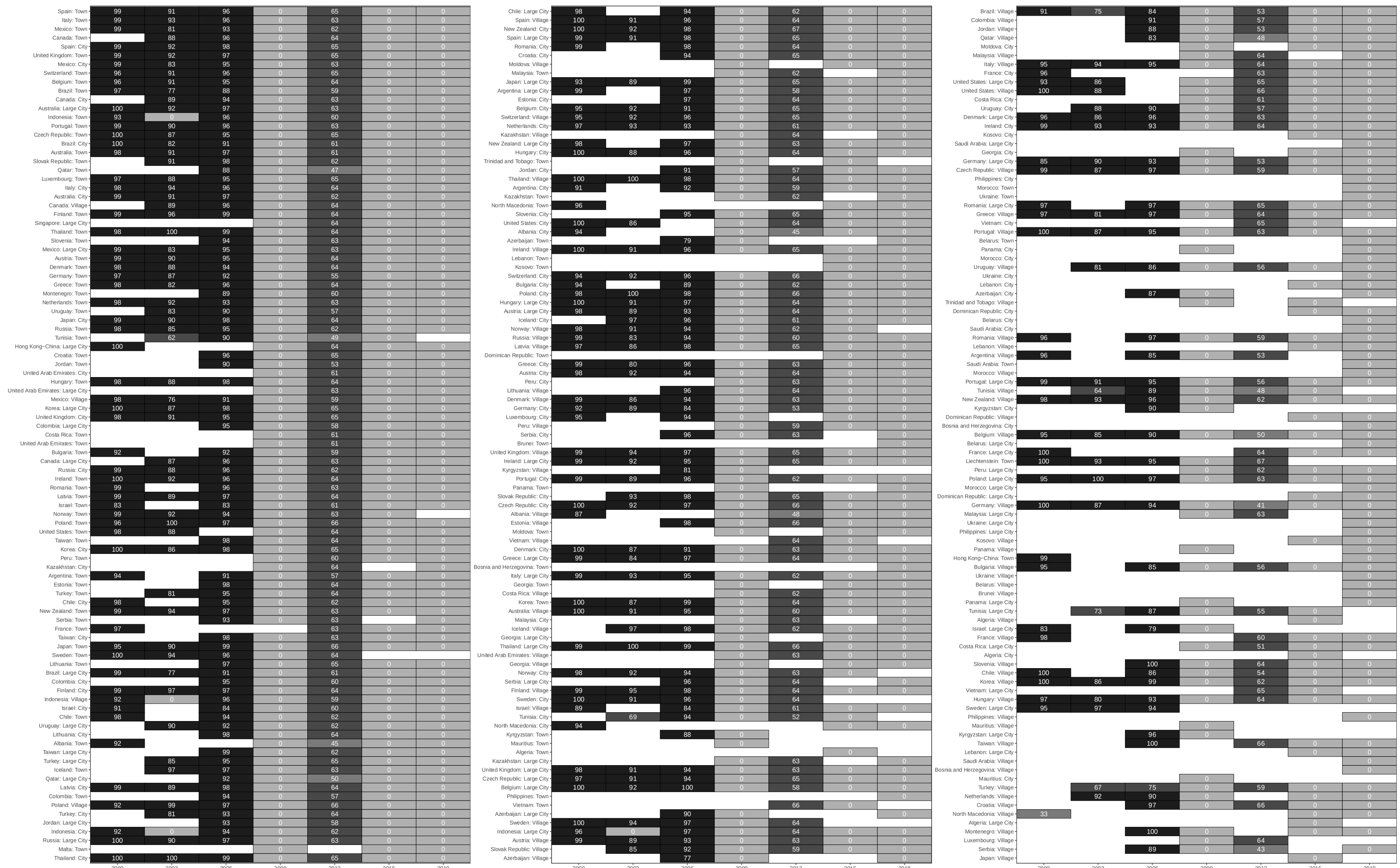


Figure F.3: Weekly Homework Hours: Data Availability by Country and Year

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

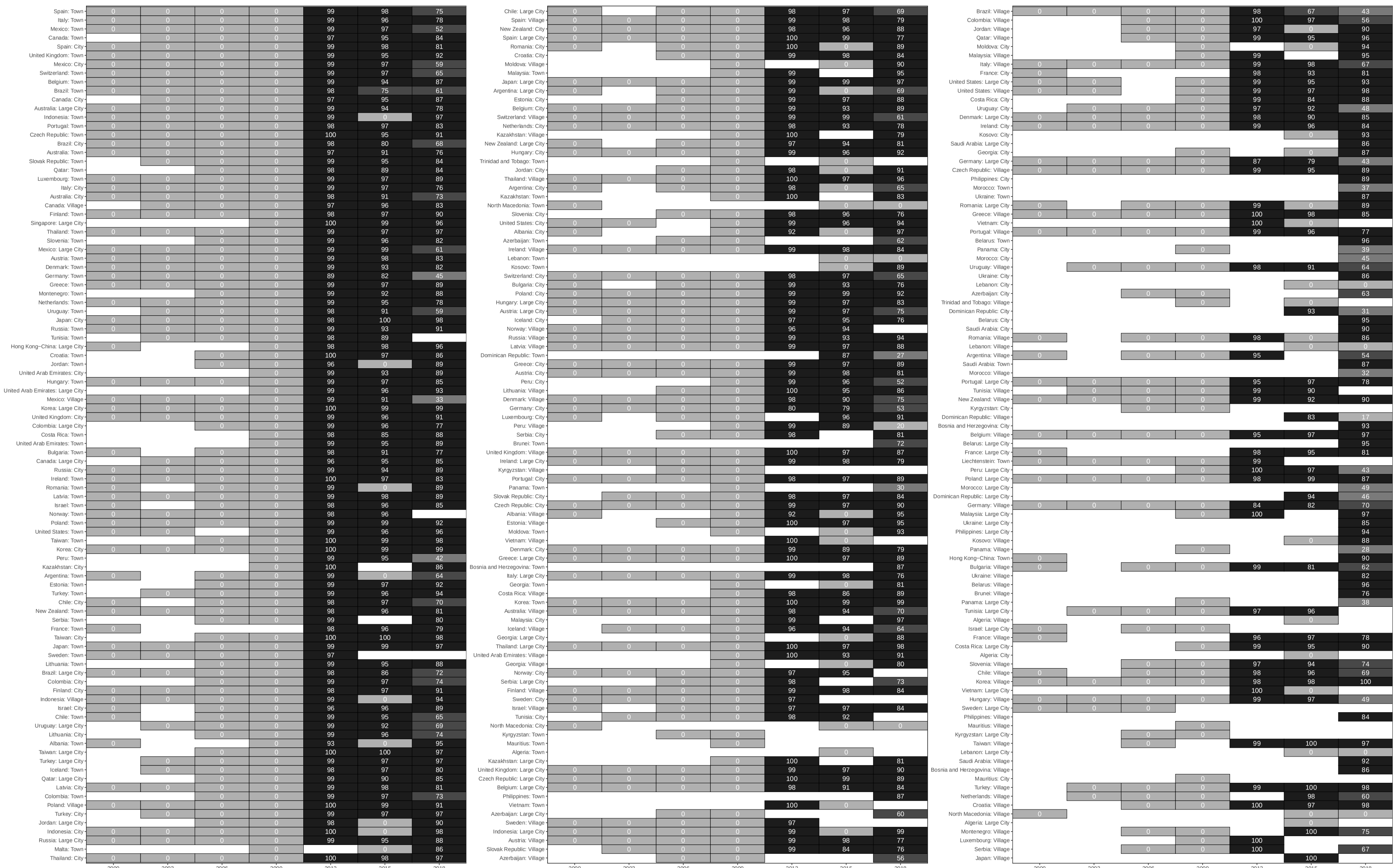


Figure F.4: Days Skipped Past 2 Weeks: Data Availability by Country and Year

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

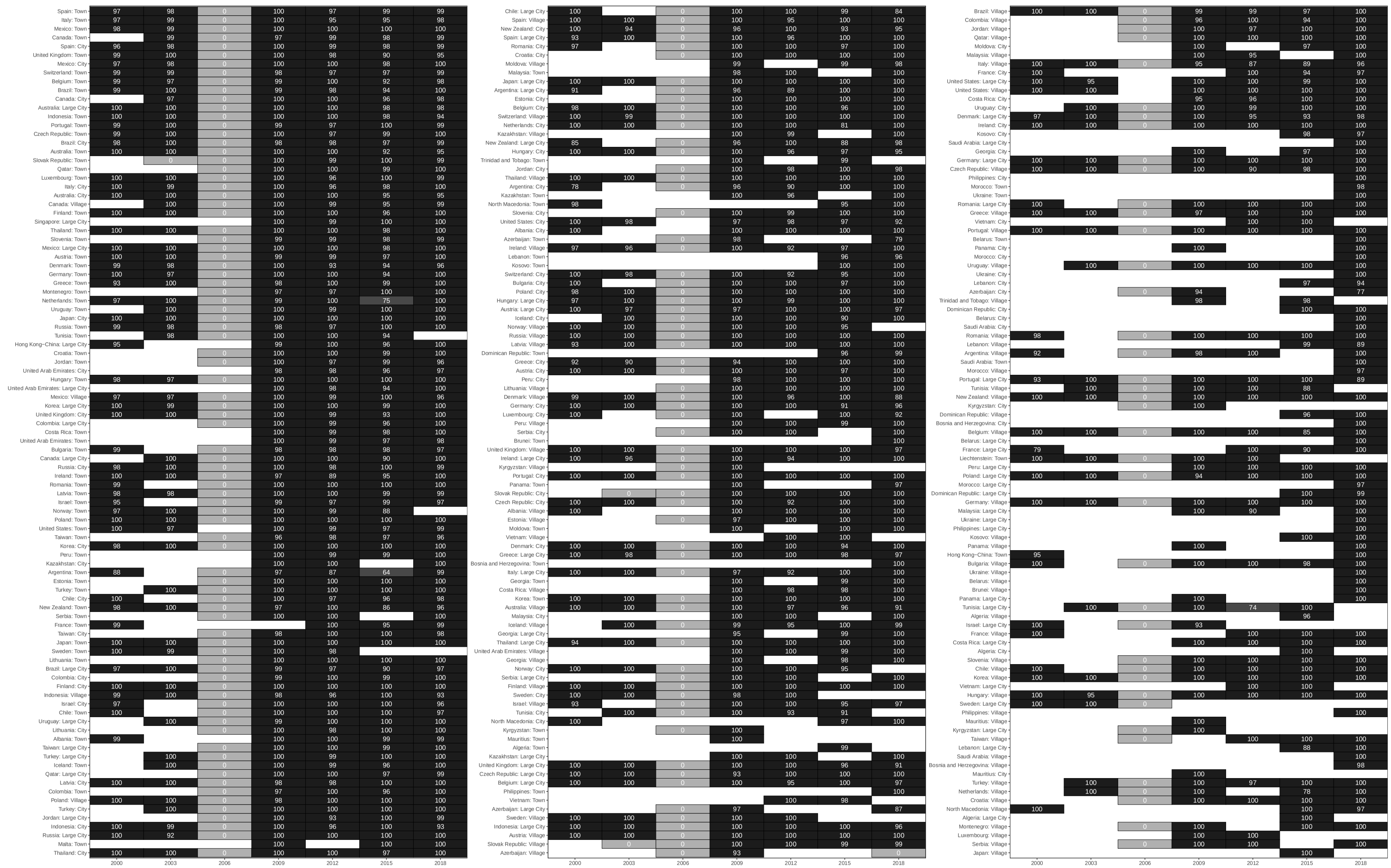


Figure F.5: Perceived Burden of Student Absenteeism: Data Availability by Country and Year

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

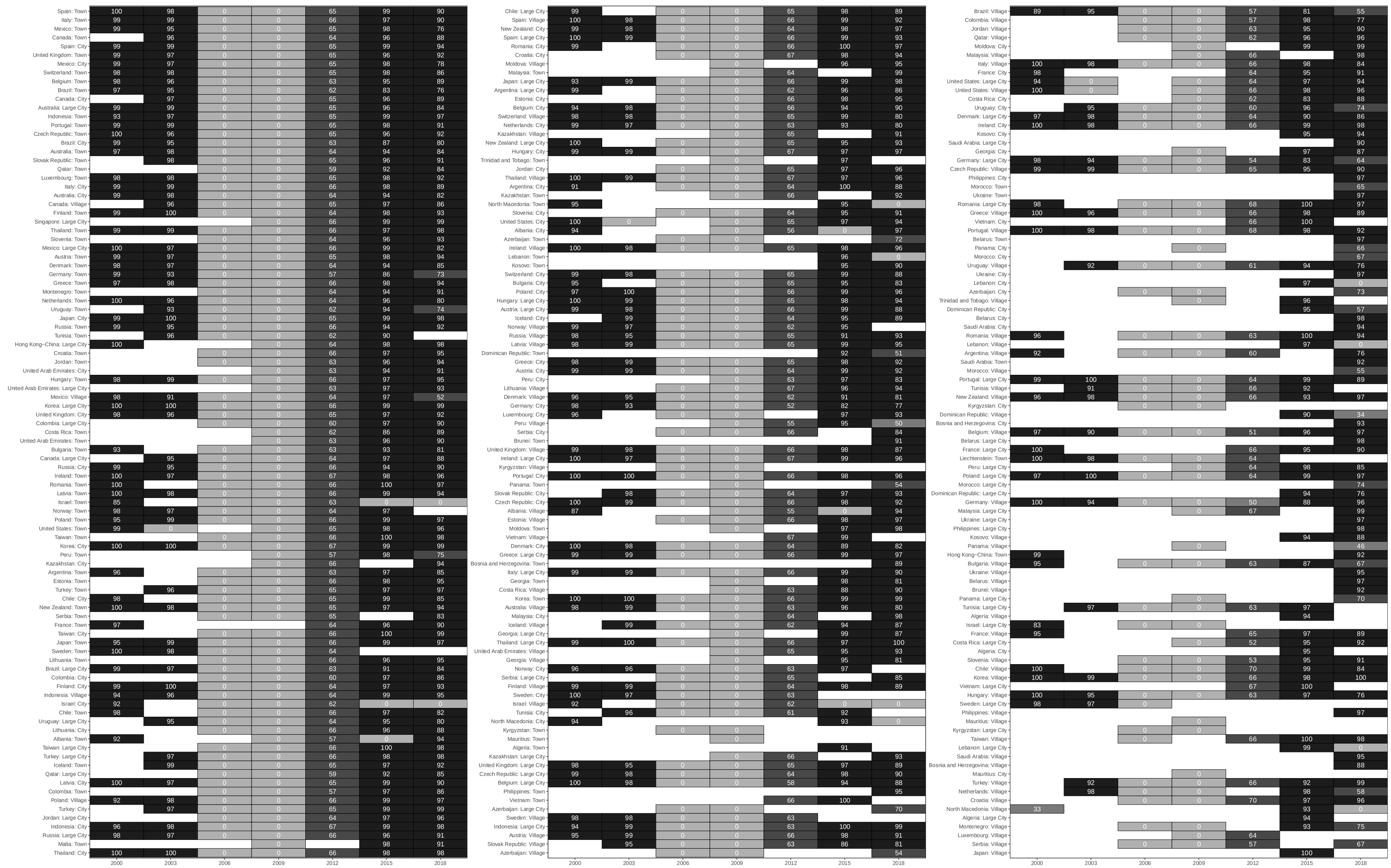


Figure F.6: Friendship Index: Data Availability by Country and Year

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

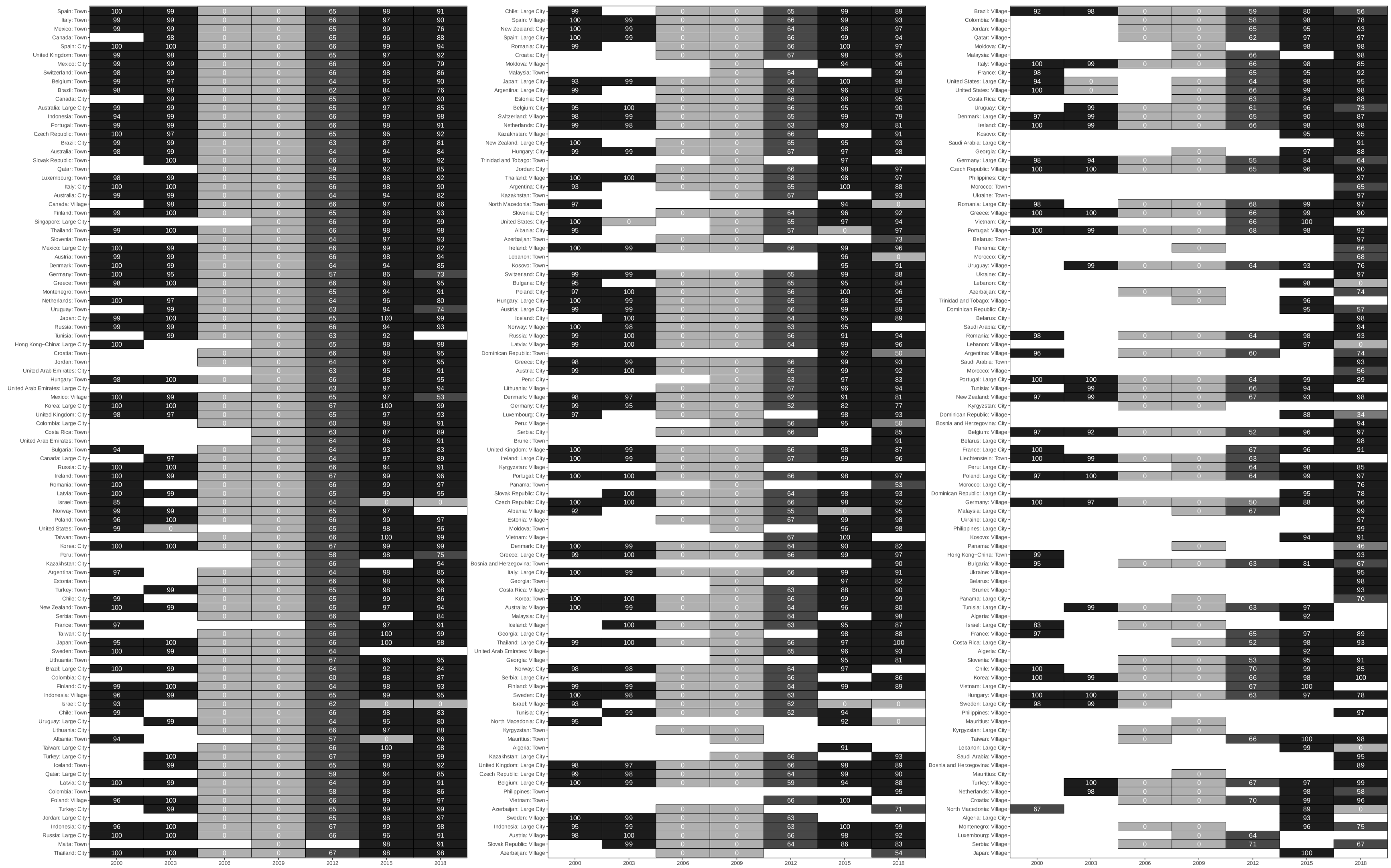


Figure F.7: Belonging Index: Data Availability by Country and Year

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

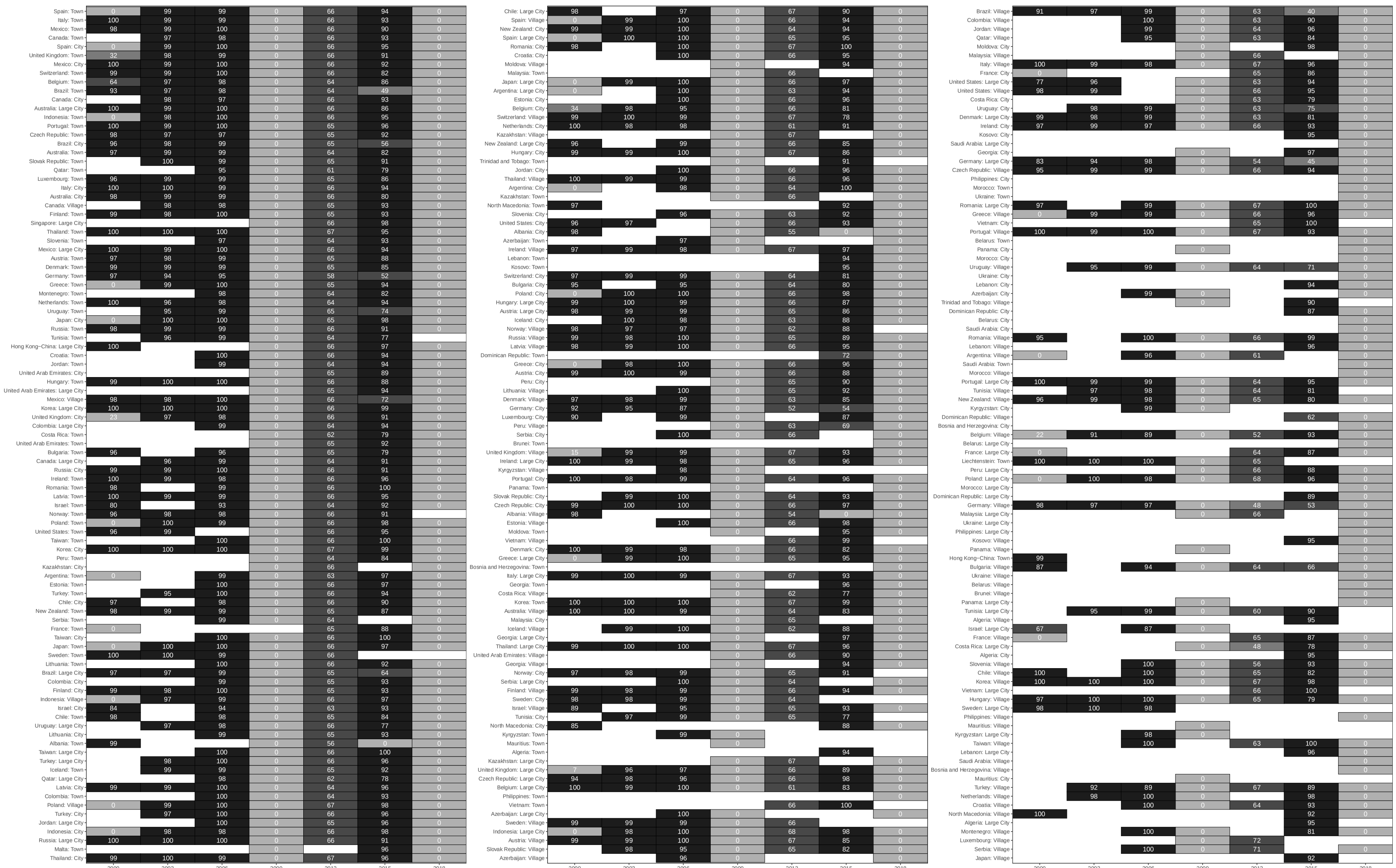


Figure F.8: Self-Efficacy Index: Data Availability by Country and Year

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