# Access to technology and educational disparity


## Abstract

The educational disparity has been a long-standing concern and grand challenge for the community. Like other sectors, the pandemic has changed the teaching and learning approaches across the globe. Although equal technology access is challenging, online learning practice offers a relatively easier avenue to minimize the disparity in academic attainment. Using purposive sampling, this study examines the effect of technology access on academic achievement. The study employs a difference in difference (DID) method and finds that technology improves educational attainment. Findings imply that technology access reduces academic disparity raised by socioeconomic differences. Therefore, policymakers could ensure technology access with sufficient training to address educational inequality-related challenges.

## 1. Introduction

Technology has become one of the key drivers of economic growth and development (Jorgenson et al., 2008; Organization for Economic Co-operation and Development, 2003; Oliner et al., 2008). In particular, the internet accelerates the spread of knowledge and information transmission. In addition, it allows networking that leads to knowledge spillovers across individuals, firms, industries, regions, and countries (Nadiri & Nandi, 2015), thus contributing to economic growth (Kenny, 2003). From a theoretical perspective, the diffusion theory (Rogers, 2003) highlights the role played by educational innovation and diffusion. However, empirical evidence has also confirmed that the effects of technology on economic growth depend on how these technologies and skills are used. In particular, more educated individuals use computers and access the internet more frequently (Keniston, 2004), leading to economic prosperity (Beecher et al., 2020).

The coronavirus has recently transformed many aspects of human lives, forcing individuals to stay home and shut down schools, businesses, and workplaces. Technology has also played a significant role in facing these challenges (Aristovnik et al., 2020). For example, as the school moved online, learners experienced profound changes. Approximately 93% of parents with K-12 children in the United States argue that their children had some online educational instruction during the pandemic. However, many in developing countries fall behind in academic status and require technical and language for internet use. In addition, socioeconomic status could also play an essential role in shaping educational attainment and professional career. For example, socioeconomic inequalities may affect access to information and knowledge associated with technology use. To address these issue, digital inclusion allows individuals to get the most recent information promptly and thereby achieve their ultimate objectives. This study examines how technology inclusion affects academic achievement despite the financial inequality of the students.

From a theoretical perspective, there are a few channels through which technology use may affect educational outcomes. For example, different individuals could have different strengths and weaknesses on various instructional topics. Internet access has the potential to offer these individual-specific instructions or educational materials, which may not be achieved in group instruction (Koedinger et al. 1997). The internet is also a valuable resource for information on various educational topics. These advantages could reduce the coordination costs of group projects. Cuban (2003) argues that computers, the internet, software, and other technologies offer interactive educational platforms to engage learners even without their physical presence altogether. Other studies - Todd & Wolpin (2003) - also argue that computer-related resources can be added as an input to a standard model for education production. However, the constraints in such models are the financial ability and skills of using these resources.

Educational achievement can also be facilitated by the irruption and diffusion of digital technologies. The uses of technological tools in the production process lead to education and training systems to offer new opportunities to integrate pedagogical resources (Gan et al., 2015), to improve communication between teachers and students (Ball, 2006; Bonal & González, 2020), to offer more flexibility across the learning process (Boelens et al., 2017), and also to reinforce the interaction between different educational resources (Collis, 1996; Fu et al., 2011, Perez, 2010).

Many studies empirically investigate the impact of technology use on educational outcomes. Angrist & Lavy (2002) pointed out that computers can be mainly used in the educational sector in two ways. First, computer skills training teaches students how to use computers, and second, computer-aided instruction uses computers to teach topics that may or may not have any relation to technology. Leuven et al. (2004), Goolsbee & Guryan (2002) find that using the computer is less effective than the conventional instructional method. In contrast, Castillo-Merino & Serradell-López (2014), Fuchs & Woessman (2004), and Noll et al. (2000) show a positive relationship between information and technological development in education. However, the technology use may also be correlated with other unobserved or imperfectly measured inputs to education. Betts (1996), Hanushek et al. (1996), and Hanushek (2006) argue how technology through investment in school affects educational outcomes. Using randomized control trials, other studies - Rouse & Krueger (2004), Banerjee et al. (2007), Mo et al. (2014) - find that limited but positive effects of the technological use on educational attainment.

As studies argue that technology use boosts educational achievement, students with lower financial ability parents could struggle compared to their higher-income counterparts. For example, Fuchs (2009), and Tselios (2011) show empirical evidence of the relationship between ICT and income inequality. Furthermore, most studies showing the effects of educational inequality on economic growth do not consider the impact of the technology used in their models (Castello & Dome'nech, 2002). A limited number of studies examine the relationship between educational inequalities and technological uses.

Using a natural experiment, this study finds that technological use improves the educational inequality between students with higher and lower socioeconomic status. Our study contributes to the literature in the following ways. First, using panel data and difference in difference (DID) methodology, this study finds that technology increases students' academic attainment by 0.12. The approach removes biases in post-technology use period comparisons between the treatment and control group of students that could result from permanent differences between those groups. It also eliminates biases from comparisons over time in the treatment group that could result from trends due to other causes of the outcome. Second, our study finds that technology reduces the inequality in academic attainments between students coming from higher and lower socioeconomic statuses. This finding is important because educational inequality is highly associated with skills gaps in adulthood (Carneiro &Heckman, 2003; Hanushek et al., 2017). Higher-income inequality would lead to delicate equality issues of opportunity and intergenerational mobility. Connolly et al. (2019) show that the link between parental income and child income increases once the child has become an adult. Finding suggests that technological inclusion reduces the gaps between educational achievements in students from higher and lower socioeconomics, reducing skill gaps in adulthood.

The rest of the paper is organized as follows. Sections 2 and d describe backgrounds and data, while methodology is described in Section 4. Section 5 reports the estimated effects of technology use on academic attainment and discusses how it reduces educational inequality. Finally, Section 6 concludes and acknowledges the potential limitation of the study.

## 2. Background

On March 20, 2020, classroom-based academic activities in Bangladesh were postponed stemming the spread of the lethal covid-19 among students. However, authorities in educational institutions, including universities, launched online classes in April 2020. There are more than 304,414 students in 46 public universities across the country.

As there was no indication when the covid situation could have ended, most universities started online classes. Moreover, students with higher socioeconomic backgrounds could easily conduct and follow courses as they mostly have electronic devices for the online instructions. In contrast, many needy pupils from remote areas could not efficiently afford online academic activities because of the lack of economic solvency. Moreover, many public university students reportedly do not have smartphones, depriving them of the opportunity to participate in online classes. And the current cost of monthly internet packages is also reportedly not feasible for needy students. Assessing realities on the ground, the University Grants Commission (UGC) of Bangladesh initiated to provide financial support with an amount of Bangladeshi Taka (BTD) 8000, equivalent to USD 93, for purchasing smartphones. Students who do not have a smartphone only could receive support. This support is considered an interest-free soft loan to be repaid by installment. The UGC will disburse the money to students through their respective universities.

Approximately 21% of the total students located in a university in Netrokona applied for the softload, the highest percentage across the county, while 3.36% is the lowest for a university located in Khulna. However, a significant share of the students in other largest universities also applied for the support loan. For example, 19.89% of the total 43,000 students in Dhaka

University, 19.18% of 7,500 students in Bangladesh University of Engineering and Technology, 17.80% of 12,921 students in Jahangirnagar University, 15.63% of 19,230 students in Jagannath University, 15% of 25,000 in Chittagong University, and 12.40% of total 38,257 students in Rajshahi University, seeks assistance from the smartphone project.

## 3. Data

We collect administrative data from one of the largest public universities, whose name remains confidential because of an agreement to access the data. This university is academically solid and well-reputed, with newly admitted students having an average high school cumulative grade point average (CGPA) of 3.51 on a scale of 4.00. Students at this university usually live in residence halls from their second year.

We purposefully chose the four largest departments with 50 students. In each department, we randomly select 25 students who have taken the government-provided smartphone, and the remaining 25 do not. Therefore, the total sample for the control group is 100, while 100 for the treatment group. In addition, we consider students who completed at least two semesters in 2020. These are the pre-intervention data. In addition, as the Bangladesh government imposes a lockdown restriction in March 2020 and allows online classes with many other inventions, we use administrative data of these students in 2021 and onwards. These are post-intervention data. As the smartphone program was initiated in 2020, we do not use any data this year. Therefore, we have five-semester academic achievements for each student: two are earlier than the intervention, and two are for post-intervention. Students who receive the smartphone soft loan are the treatment group, while students without the loan are the control group. In addition, we survey these students about their other information like technological skills, study duration, and internet speeds each semester.

Table 1 shows the summary statistics of the variables. Following standard literature on the education of economics, we use the CGPA to measure academic achievement quantitatively. The average CGPA of the whole sample is 3.12, while 2.94 for the control group and 3.30 for the treatment group. Likewise, the average family income, measured in Bangladeshi Taka (BTD) thousands, of the entire sample is 39.69, while it is similar for both groups. A higher standard deviation of the average income represents a higher variation in the family earnings.

Table 1 also shows the average technology use hours for education purposes. For example, on average, 2.18 hours are spent for educational purposes for the whole sample, while 2.11 and 2.25 hours for control and treatment groups, respectively. On average, family members of the students in the control group use 3.35 hours, during 4.01 hours for the treatment group. To quantify the socioeconomic (SES) indicator, we consider an income and educational status index. We first classify family educational attainment and income into five categories in such a case. The

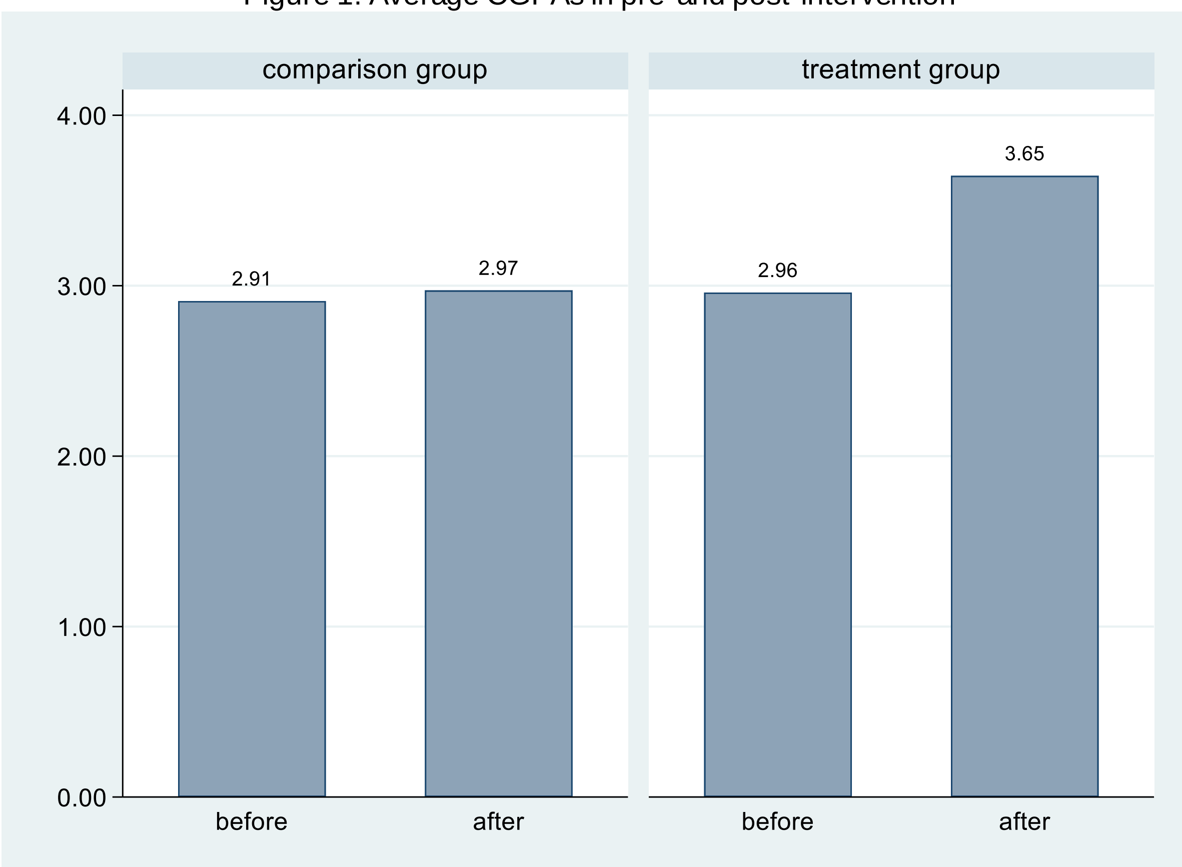
Table 1: Descriptive Statistics

| | *Full Sample* | | *Control Group* | | *Treatment Group* | |
|---|---|---|---|---|---|---|
| | Mean | Standard deviation | Mean | Standard deviation | Mean | Standard deviation |
| CGPA | 3.1219 | 0.4160 | 2.9412 | 0.3610 | 3.3025 | 0.3883 |
| Family income | 39.6904 | 35.0113 | 39.8795 | 35.0334 | 39.5014 | 35.0320 |
| Self tech use hours | 2.1782 | 0.5993 | 2.1055 | 0.5372 | 2.2509 | 0.6481 |
| Family tech use hours | 3.6969 | 1.7938 | 3.3455 | 1.4436 | 4.0484 | 2.0278 |
| Internet speed | 3.0344 | 1.0311 | 3.0064 | 0.9973 | 3.0623 | 1.0644 |
| SES index | 4.1425 | 2.3779 | 4.1625 | 2.3812 | 4.1225 | 2.3773 |
| Tech skills | 5.1950 | 2.5525 | 5.1450 | 3.2704 | 5.2450 | 1.5316 |

highest category is denoted by indicator 5.00, and consequently, the lowest type is 1.00. We then average these two values to measure the SES of students. The average index for the SES is 4.14 for the whole sample, while 4.16 and 4.12 for the control and treatment groups, respectively. Technological skills could also play a significant role in online instructions. We use a scale of 10 for the excellent skills and consequently 1 for the poorest skills. The average skills for the whole sample are 5.20, while it is 5.15 and 5.25 for the control and treatment groups, respectively. These statistics indicate that treatment and control groups students have moderate skills in using the technology.

Figure 1 shows the average of the outcome variables for the control and treatment groups. The average CGPA is 2.91 for the control group before the intervention while 2.97 after the intervention. The average values of the treatment group are 2.96 and 3.65, respectively. The average CGPA difference between the treatment and control group in the pre-intervention period is 0.05. Using the *t*-significance test, this difference is not statistically significant, indicating that the treatment and control groups are likely to be similar before the program intervention. On the other hand, the post-intervention difference between the treatment and control group is 0.68 and is statistically significant. These results indicate that the smartphone intervention program could significantly impact the academic outcome.

Figure 1: Average CGPAs in pre-and post-intervention




Note: This Table shows the average CGPAs of the treatment and control groups.

One advantage of using this data is that they have multiple periods of panel data. Another advantage of these administrative data is that they likely to have a lower measurement error than survey data. However, one drawback of using this data set is that family earnings are not fully observed. While there would have a particular concern if CGPA or family earnings were endogenous to other variables, individual-specific effects could control this effect.

## 4. Methodology

### 4.1 Difference in Difference Model

To identify the effect of technology on the academic outcome, we exploit a quasi-natural experiment offered by Bangladesh. For example, the Bangladesh government provided a soft loan for buying technology for online education. Students who received this opportunity are in the treatment group, and students without a smartphone are in the control group. The variations of difference in difference (DID) estimation mainly come from intervention, allowing to compare the difference in academic achievement between beneficiaries and non-beneficiaries before and after the program. To examine the treatment effect, we specify the DID estimation as follows:

$$y_{it} = \alpha_0 + \alpha_1 time_{it} + \alpha_2 treat_{it} + \delta\, treat_{it} * time_{it} + X'_{it}\beta + d_i + \lambda_t + e_i, \quad (1)$$

where, $y_{it}$ is the CGPA of student $i$ in $t$ semester; $treat_{it}$ a binary indicator for receiving government smartphone, otherwise *0;* $time_{it}$ is the binary indicator after student $i$ gets the smartphone in *t* semester, otherwise *0;* $X_{it}{}'$ is the vector for control variables, such as financial capital, digital literacy, and experience in the same business. The $d_i$ denotes the district fixed effects, controlling for the time-invariant characteristic of different cities, such as geographic factors. The $\lambda_t$ denotes the Covid fixed effects to capture the factors that affect the academic outcome in a given year. The outcome variable is the CGPA. The coefficient of interest, $\delta$, is the DID estimator, representing the impacts of smartphones on academic outcomes. The DID estimate is expected to be positive and statistically significant, indicating that smartphone intervention effectively increases educational outcomes. Using the Event Study design, Figure A1 in the appendix that the parallel trends assumption is satisfied.

## 5. Results

Table 2 shows the treatment effect of the smartphone on academic attainment. Column 1 shows that the estimated impact of the smartphone phone is 0.36, and it is significant. This model does not consider any control variable or any other fixed effects. A positive and significant impact represents that smartphone significantly improves academic attainment. Students with smartphones receive higher grades than their counterpart students by 0.36. Other factors could also affect educational achievement. Column 2 incorporates family income into the same model.

Table2: the estimated effects of the mobile phone academic achievement from the DID model

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| treatment | 0.3613*** | 0.3610*** | 0.4287** | 0.4144*** | 0.4114*** | 0.3490*** | 0.3484*** | 0.3194*** | 0.3414*** |
| | (0.0371) | (0.0372) | (0.2180) | (0.1085) | (0.1086) | (0.0871) | (0.0872) | (0.0840) | (0.0772) |
| Income | | -0.0008** | -0.0012*** | 0.0006*** | 0.0002 | 0.0003 | 0.0003 | 0.0004 | 0.0003 |
| | | (0.0004) | (0.0004) | (0.0002) | (0.0005) | (0.0004) | (0.0004) | (0.0004) | (0.0003) |
| | | | | (0.0154) | (0.0154) | (0.0161) | (0.0165) | (0.0163) | (0.0156) |
| SES index | | | | | 0.0060 | 0.0012 | 0.0012 | 0.0003 | -0.0017 |
| | | | | | (0.0063) | (0.0051) | (0.0051) | (0.0048) | (0.0044) |
| Self tech use hours | | | | | | 0.2682*** | 0.2680*** | 0.1542*** | 0.0069 |
| | | | | | | (0.0147) | (0.0147) | (0.0200) | (0.0231) |
| Tech Skill | | | | | | | 0.0001 | 0.0002 | 0.0000 |
| | | | | | | | (0.0002) | (0.0002) | (0.0002) |
| Family tech use hours | | | | | | | | 0.0513*** | 0.0705*** |
| | | | | | | | | (0.0064) | (0.0061) |
| Search numbers | | | | | | | | 0.0045 | 0.0238*** |
| | | | | | | | | (0.0085) | (0.0080) |
| Internet speed | | | | | | | | | 0.1144*** |
| | | | | | | | | | (0.0109) |
| Individual FE | | | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Semester FE | | | | Yes | Yes | Yes | Yes | Yes | Yes |
| Constant | 2.9412*** | 2.9750*** | 2.9578*** | 2.6315*** | 2.6208*** | 2.1629*** | 2.1609*** | 2.2343*** | 2.0692*** |
| | (0.0262) | (0.0302) | (0.1547) | (0.0776) | (0.0784) | (0.0677) | (0.0682) | (0.0827) | (0.0776) |
| *N* | 800 | 800 | 800 | 800 | 800 | 800 | 800 | 800 | 800 |

Note. ***, **, and * denote significant at 1%, 5%, and 10%, respectively. The robust standard error is clustered at the departent level.

A significant impact of income indicates that students from a higher family income could also have higher grades. The estimated effect of the treatment is also significant, meaning that smartphone increases students' academic attainments.

The ability of individual students could be different than other students. Therefore, the individual ability could also affect their attainment. Similarly, students take various courses with different instructors in different semesters. We control individual fixed and semester fixed effects to capture these fixed effects. Columns 3 and onwards report the estimated results with these fixed effects. For example, Column 4 shows the estimated impact of treatment with controlling individual fixed effects. The positive and significant results indicate that smartphone increases students' academic attainments.

**Does technological inclusion reduce educational disparity?**

We choose students from similar geographical areas to answer whether technological inclusion decreases the educational disparity between students with higher and lower parental income. We mainly consider the district as an indicator for the same geographical areas. We find that the 36 pairs of students in the control group came from a similar location, and 29 pairs from the treatment group. The family income differences for each student pair are considered socioeconomic status differences. The remaining students in both groups are excluded from this estimation procedure. We assume that the differences in GPAs for the pair of students are a proxy for the educational disparity. To confirm whether socioeconomic differences affect the disparity in students' achievements, we use a pooled ordinary least square (POLS) model. We find that the estimated effects of the socioeconomic difference are positive and statistically significant. This significant effect implies that SES increases disparity in academic achievement.

To examine whether technological inclusion affects academic disparity, we employ the following model:

$$y_{jt} = \alpha_0 + \alpha_1 time_{jt} + \delta\, treat_{jt} + \delta\, time_{jt} * treat_{jt} + X'_{jt}\beta + d_j + \lambda_t + e_j, \qquad (2)$$

where, $y_{jt}$ is the CGPA differences of *j* pair of student $i$ in $t$ semester*;* $treat_{jt}$ a binary indicator for receiving a government smartphone, otherwise *0; time* is the binary indicator after students $j$ get the smartphone, otherwise *0;* $X_{jt}{}'$ is the vector for differences in control variables. The coefficient of interest, $\delta$, is the DID estimator, representing the impacts of smartphones on the business outcomes. The DID estimate is expected to be negative, indicating that smartphone intervention effectively decreases educational disparity in GPAs.

Table 3 shows the impact of the smartphone on the difference in academic attainment. Column 1 shows the estimated effect is negative and statistically significant. This impact means that smartphones reduce educational achievement differences between students from higher and lower socioeconomic statuses. We also control the individual and semester fixed effects by incorporating more variables into the model; we still find the estimated treatment effect is negative and significant.

Table 3: Impact of the smartphone on the difference in academic attainment

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| treatment | -0.1212*** | -0.1101** | -0.1004*** | -0.1231*** | -0.1317*** | -0.1204*** |
| | (0.0091) | (0.0012) | (0.0103) | (0.0109) | (0.0201) | (0.0109) |
| Self Tech Use hours | | | | 0.1001*** | 0.1210*** | 0.1121*** |
| | | | | (0.0117) | (0.098) | (0.0112) |
| Tech use hours | | | | | 0.0111 | 0.0128 |
| | | | | | (0.0032) | (0.0042) |
| Family tech Use hours | | | | | | 0.0871*** |
| | | | | | | (0.0231) |
| Search numbers | | | | | | 0.0847 |
| | | | | | | (0.0901) |
| Individual FE | | Yes | Yes | Yes | Yes | Yes |
| Semester FE | | | Yes | Yes | Yes | Yes |
| Constant | 2.9412*** | 2.9578*** | 2.6315*** | 2.1629*** | 2.1609*** | 2.2343*** |
| | (0.0262) | (0.1547) | (0.0776) | (0.0677) | (0.0682) | (0.0827) |
| N | 260 | 260 | 260 | 260 | 260 | 260 |

Note. ***, **, and * denote significant at 1%, 5%, and 10%, respectively. The robust standard error is clustered at the department level.

### 6. Conclusion

The educational disparity has been a long-standing concern and grand challenge for the community. Like other sectors, the pandemic has changed the teaching and learning approaches across the globe. Although equal technology access is challenging, online learning practice offers a relatively easier avenue to minimize the disparity in academic attainment. The study employs a difference in difference (DID) method and finds that technology improves educational attainment. Findings imply that technology access reduces academic disparity raised by socioeconomic differences. Therefore, policymakers could ensure technology access with sufficient training to address educational inequality-related challenges.

**References**


Angrist, J., & Lavy, V. (2002). New evidence on classroom computers and pupil learning. *The Economic Journal*, *112*(482), 735-765.

Aristovnik, A., Keržič, D., Ravšelj, D., Tomaževič, N., & Umek, L. (2020). Impacts of the COVID-19 pandemic on life of higher education students: A global perspective. *Sustainability*, *12*(20), 8438.

Ball, S. B., Eckel, C., & Rojas, C. (2006). Technology improves learning in large principles of economics classes: Using our WITS. *American Economic Review*, *96*(2), 442-446.

Banerjee, A. V., Cole, S., Duflo, E., & Linden, L. (2007). Remedying education: Evidence from two randomized experiments in India. *The Quarterly Journal of Economics*, *122*(3), 1235-1264.

Beecher, B., Streitwieser, B., & Zhou, J. (2020). Charting a new path toward economic prosperity: Comparing policies for higher education hubs in Hong Kong and South Korea. *Industry and Higher Education*, *34*(2), 80-90.

Boelens, R., De Wever, B., & Voet, M. (2017). Four key challenges to the design of blended learning: A systematic literature review. *Educational Research Review*, *22*, 1-18.

Bonal, X., & González, S. (2020). The impact of lockdown on the learning gap: family and school divisions in times of crisis. *International Review of Education*, *66*(5), 635-655.

Carneiro, P., & Heckman, J. (2003). *Human Capital Policy* (No. 821). Institute of Labor Economics (IZA).

Castillo-Merino, D., & Serradell-López, E. (2014). An analysis of the determinants of students' performance in e-learning. *Computers in Human Behavior*, *30*, 476-484.

Connolly, M., Haeck, C., & Lapierre, D. (2019). *Social mobility trends in Canada: going up the Great Gatsby curve* (No. 19-03). Research Group on Human Capital-Working Paper Series.

Fu, X., Pietrobelli, C., & Soete, L. (2011). The role of foreign technology and indigenous innovation in the emerging economies: technological change and catching-up. *World Development*, *39*(7), 1204-1212.

Fuchs, T., & Woessmann, L. (2004). *Computers and student learning: Bivariate and multivariate evidence on the availability and use of computers at home and at school* (No. 1321). CESIFO working paper.

Gan, B., Menkhoff, T., & Smith, R. (2015). Enhancing students' learning process through interactive digital media: New opportunities for collaborative learning. *Computers in Human*

*Behavior*, *51*, 652-663.

Goolsbee, A., & Guryan, J. (2002). The Impact of Internet Subsidies in Public Schools. NBER Working Paper Series.

Hanushek, E. A., Ruhose, J., & Woessmann, L. (2017). Knowledge capital and aggregate income differences: Development accounting for US states. *American Economic Journal: Macroeconomics*, *9*(4), 184-224.

Leuven, E., Lindahl, M., Oosterbeek, H., & Webbink, D. (2007). The effect of extra funding for disadvantaged pupils on achievement. *The Review of Economics and Statistics*, *89*(4), 721-736.

Perez, C. (2010). Technological revolutions and techno-economic paradigms. *Cambridge journal of economics*, *34*(1), 185-202.

Rouse, C. E., & Krueger, A. B. (2004). Putting computerized instruction to the test: A randomized evaluation of a "scientifically based" reading program. *Economics of Education Review*, *23*(4), 323-338.

Sosin, K., Lecha, B. J., Agarwal, R., Bartlett, R. L., & Daniel, J. I. (2004). Efficiency in the use of technology in economic education: Some preliminary results. *American Economic Review*, *94*(2), 253-258.

**Appendix**

Figure A1: The results of the parallel trend test