Does Economic Development Benefit Internet Use?

A Cross-National Comparison of Students' Daily Life Experiences with Information and Communication Technologies, Using **PISA** 2009

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INTRODUCTION

The Development and Extensive Use of Digital Technologies

Its effects on:

- educational outcomes
- economic returns
- health
- social relationships

The Prevalence of Digital Use among Young Population

Focus:

- its effects on student learning process
- how students use digital technologies
- the socioeconomic gap in digital use

The Global Digital Divide

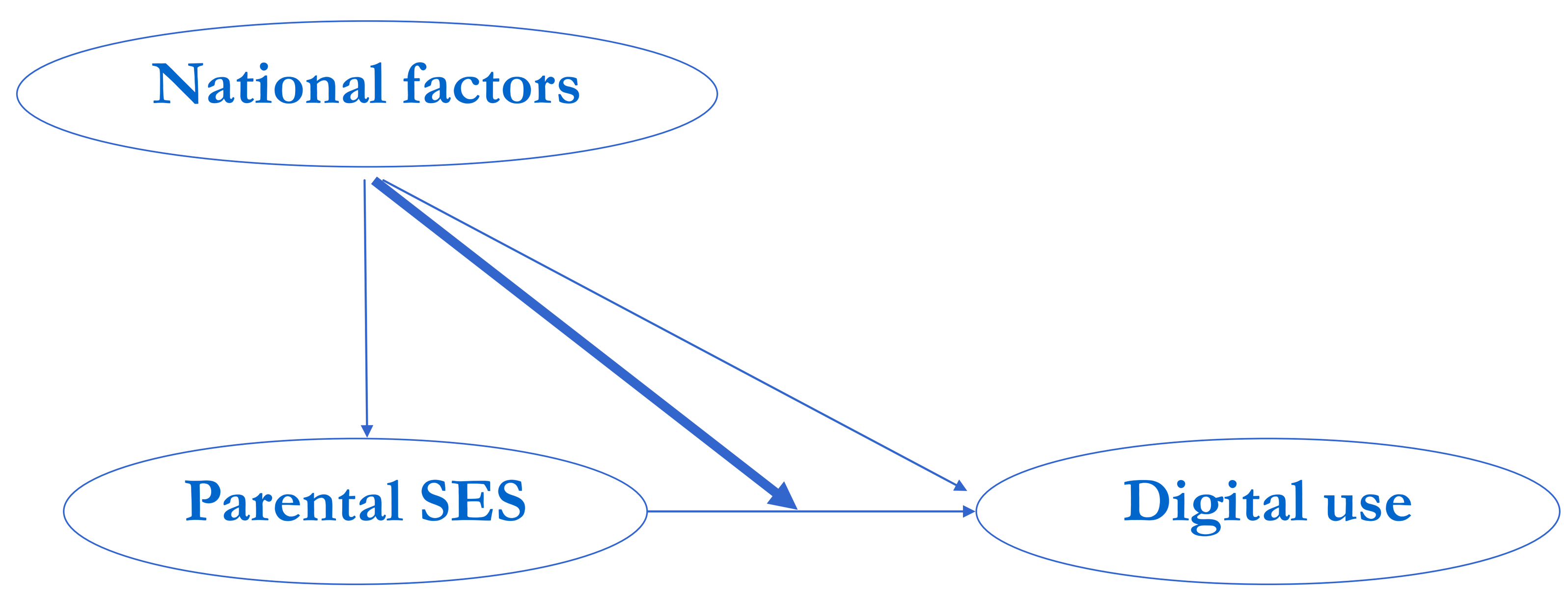
Economic factors as a key in the process of technology diffusion:

- country-level: economic development between countries
- individual-level: one's income status within countries

RESEARCH FRAMEWORK

Research Questions

1. How do economic growth and income inequality affect students' digital access and usage?
2. Do increased economic growth and reduced inequality affect the pattern and the dynamic of digital gap between students from high SES versus low SES families?



Two Types of Economic Factors

- Average national income between countries
  - GDP per capita
- Income gap within countries
  - Gini index

High income countries: SES → Digital use

Low income countries: SES → Digital use

More unequal countries: SES → Digital use

Less unequal countries: SES → Digital use

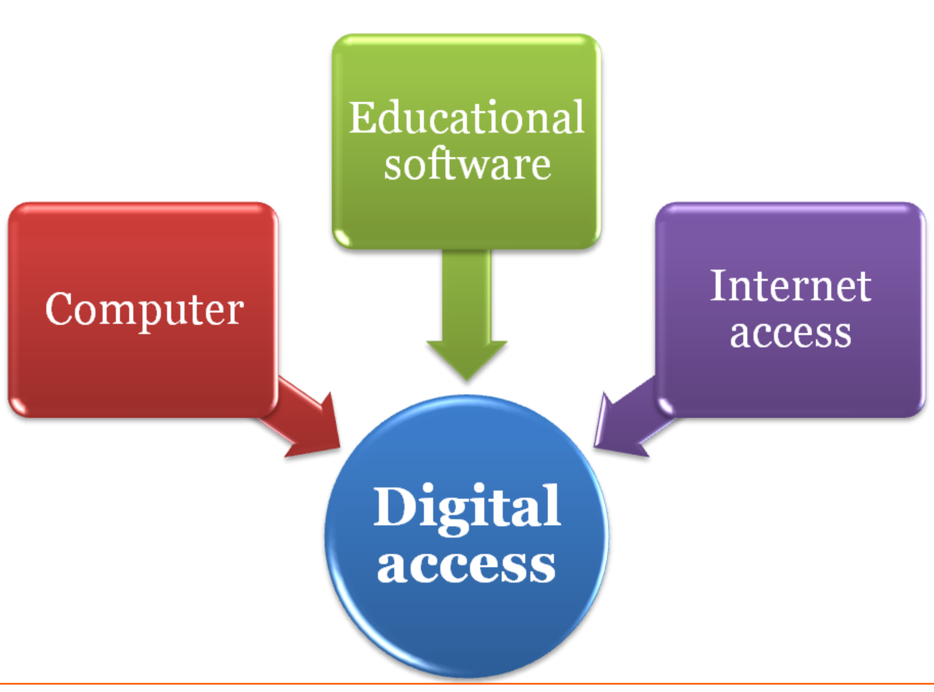
DATA, MEASURES, AND METHODS

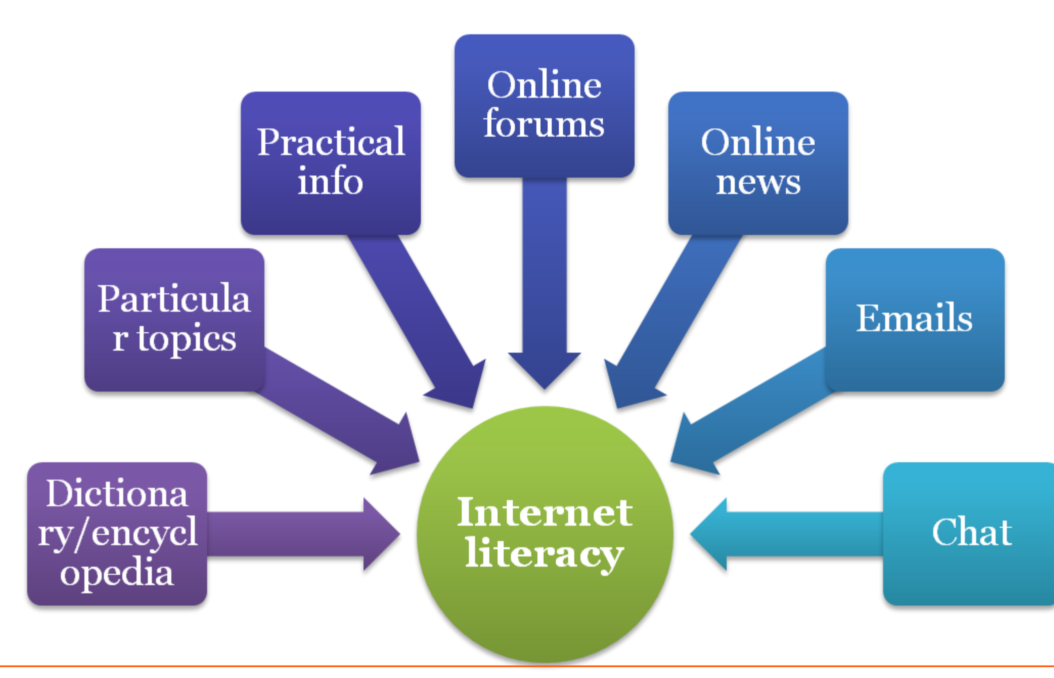
OECD Programme for International Student Assessments (**PISA**)

- data year 2009
- 15-year old pupils' real life situations
- 348,794 respondents across 41 countries

Hierarchical Linear Modeling (**HLM**)

- random slope models
- level 1: individual-level variables
- level 2: country-level cluster variables





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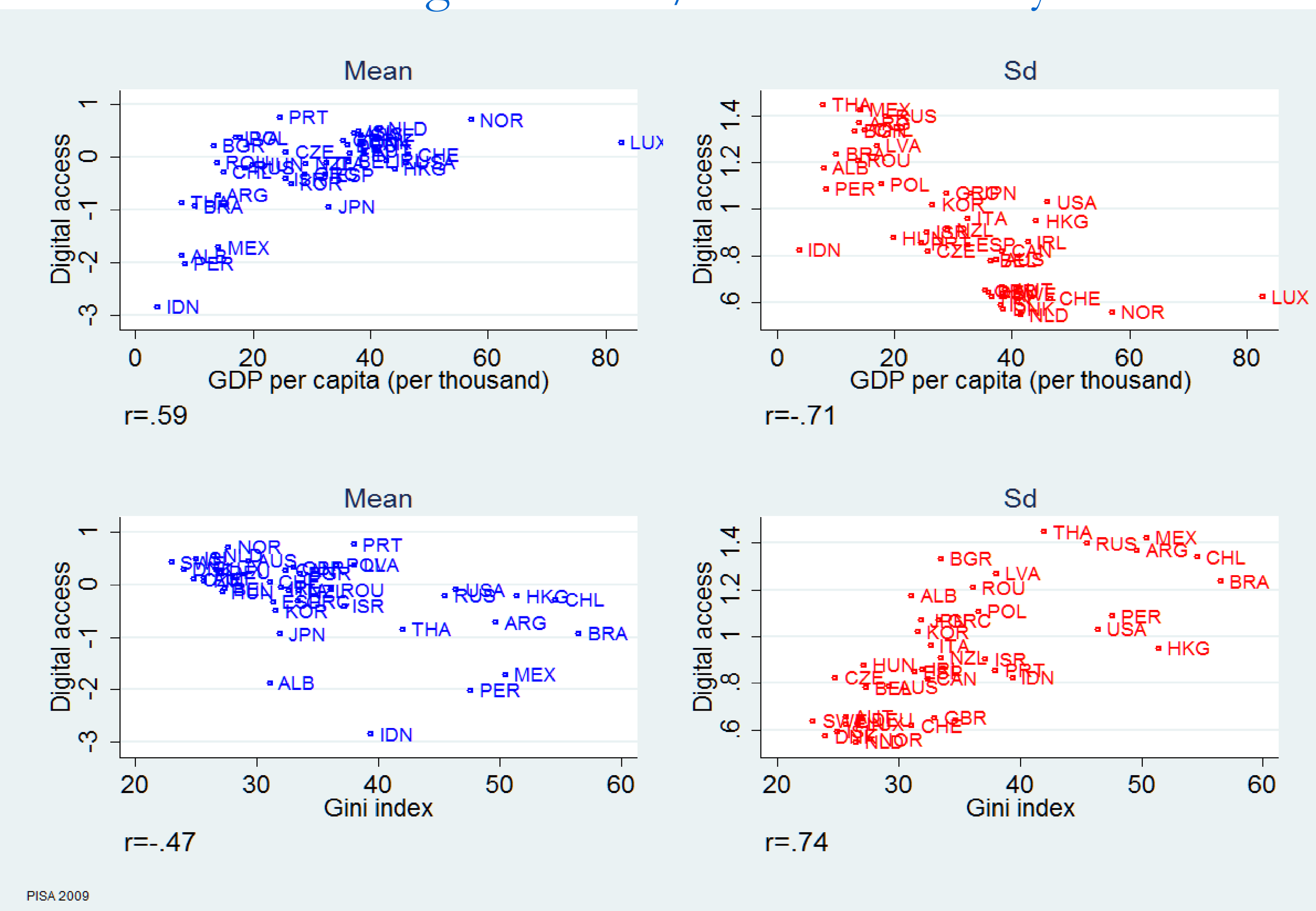
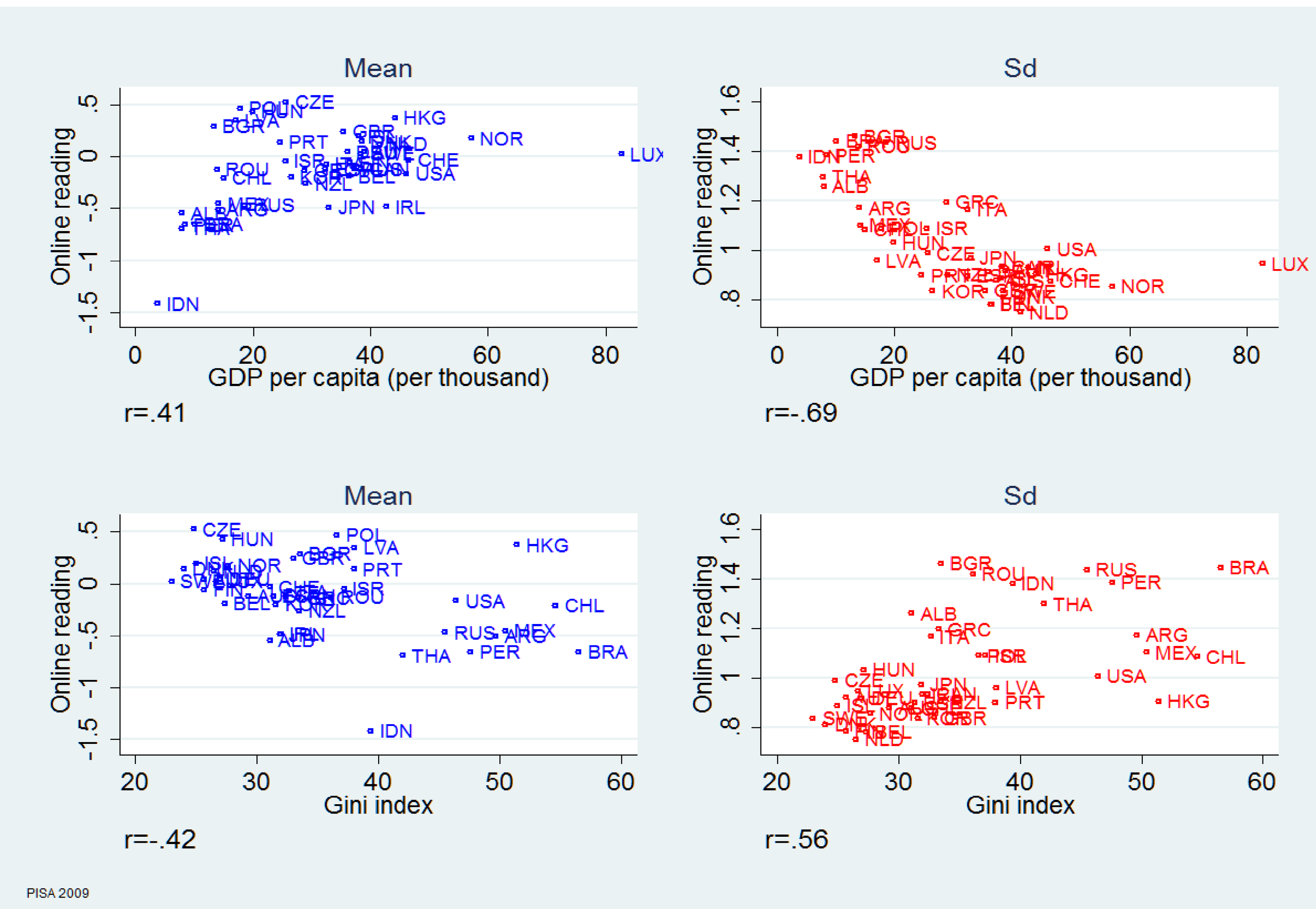
RESULTS

STEP 1: Bivariate Relationships between National Characteristics and Digital Access/Internet Literacy





STEP 2: HLM (Baseline Models)

Table 1. The Effects of Students' Background Characteristics on Digital Access at Home and Internet Literacy

	Digital access at home			*Internet literacy*		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Male		0.061**	0.022**		0.053**	0.032**
		(0.003)	(0.003)		(0.004)	(0.003)
Single-parent family		-0.283**	-0.147**		-0.072**	0.005
		(0.004)	(0.004)		(0.005)	(0.005)
Other family		-0.281**	-0.110**		-0.177**	-0.080**
		(0.009)	(0.008)		(0.010)	(0.009)
First generation		-0.281**	-0.034**		0.035**	0.176**
		(0.009)	(0.007)		(0.009)	(0.009)
Second generation		-0.238**	0.064**		0.035**	0.208**
		(0.008)	(0.007)		(0.009)	(0.009)
Village		-0.377**	-0.123**		-0.416**	-0.271**
		(0.007)	(0.006)		(0.007)	(0.007)
Small town		-0.163**	-0.042**		-0.147**	-0.078**
		(0.005)	(0.004)		(0.005)	(0.005)
City		0.207**	0.065**		0.160**	0.079**
		(0.005)	(0.004)		(0.005)	(0.005)
Large city		0.375**	0.155**		0.268**	0.142**
		(0.006)	(0.006)		(0.007)	(0.007)
Parent SES			0.534**			0.305**
			(0.001)			(0.002)
Intercept		-0.191	-0.131		-0.125*	-0.091+
		(0.122)	(0.086)		(0.059)	(0.047)
var (Intercept)	0.571	0.592	0.297	0.141	0.141	0.089
sigma	1.011	0.958	0.701	1.120	1.087	1.003
ICC	0.361	0.382	0.298	0.112	0.115	0.082

Data Source. PISA, 2009.

Notes. N = 348,794 (41 countries). Standard errors are in parentheses. All coefficients are adjusted by multiple imputations for missing cases in controls (m = 1). Female, Two-parent family, Native, and Town are reference categories.

+ $p < .1$, * $p < .05$, ** $p < .01$ (2-*tailed*).

STEP 3: HLM (Main Models)

Table 2. The Effects of Economic Development and Income Inequality on Digital Access at Home

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Individual level factors:						
Other control variables[a]		yes		yes	yes	yes
Parent SES		0.534**		0.534**	0.506**	0.524**
		(0.001)		(0.001)	(0.031)	(0.022)
Country-level factors:[b]						
GDP (log)	0.903**	0.521**			0.518**	0.517**
	(0.126)	(0.110)			(0.136)	(0.136)
Gini (log)			-1.511**	-0.733*	0.020	0.020
			(0.427)	(0.336)	(0.353)	(0.353)
Cross-level interactions:						
GDP (log) × Parent SES						-0.114**
						(0.041)
Gini (log) × Parent SES						0.362**
						(0.107)
Intercept	-0.225**	-0.133+	-0.287**	-0.162+	-0.076	-0.076
	(0.079)	(0.069)	(0.105)	(0.083)	(0.074)	(0.074)
var (Intercept)	0.254	0.193	0.437	0.266	0.208	0.208
var (Parent SES)					0.039	0.019
sigma	1.011	0.701	1.011	0.701	0.669	0.669
ICC[c]	0.201	0.215	0.302	0.275	0.237	0.237

Data Source. PISA, 2009.

Notes. N = 348,794 (41 countries). Standard errors are in parentheses. All coefficients are adjusted by multiple imputations for missing cases in controls (m = 1). [a]Other control variables include Male, Single-parent family, Other family, 1st generation, 2nd generation, Village, Small town, City, and Large city. [b]all country-level variables are grand mean centered. [c]ICC for an empty model: 0.361.

Table 3. The Effects of Economic Development and Income Inequality on Internet Literacy

	Model 1	Model 2	Model 3	Model 4	Model 5
Individual level factors:					
Other control variables[a]			yes	yes	yes
Digital access at home			0.314**	0.314**	0.314**
			(0.002)	(0.002)	(0.002)
Parent SES			0.124**	0.134**	0.126**
			(0.019)	(0.017)	(0.014)
Country-level factors:[b]					
GDP (log)	0.349**		-0.178**		-0.179**
	(0.077)		(0.064)		(0.064)
Gini (log)		-0.673**	-0.196	0.053	-0.197
		(0.219)	(0.165)	(0.151)	(0.165)
Cross-level interactions:					
GDP (log) × Parent SES					-0.130**
					(0.025)
Gini (log) × Parent SES				0.207**	0.024
				(0.070)	(0.065)
Intercept	-0.120*	-0.148**	-0.016	-0.006	-0.016
	(0.048)	(0.054)	(0.034)	(0.037)	(0.034)
var (Intercept)	0.094	0.115	0.045	0.054	0.045
var (Parent SES)			0.014	0.012	0.007
sigma	1.120	1.120	0.917	0.917	0.917
ICC[c]	0.077	0.093	0.047	0.055	0.047

Data Source. PISA, 2009.

Notes. N = 348,794 (41 countries). Standard errors are in parentheses. All coefficients are adjusted by multiple imputations for missing cases in controls (m = 1). [a]Other control variables include Male, Single-parent family, Other family, 1st generation, 2nd generation, Village, Small town, City, and Large city. [b]all country-level variables are grand mean centered. [c]ICC for an empty model: 0.112.

STEP 4: Post-Estimations

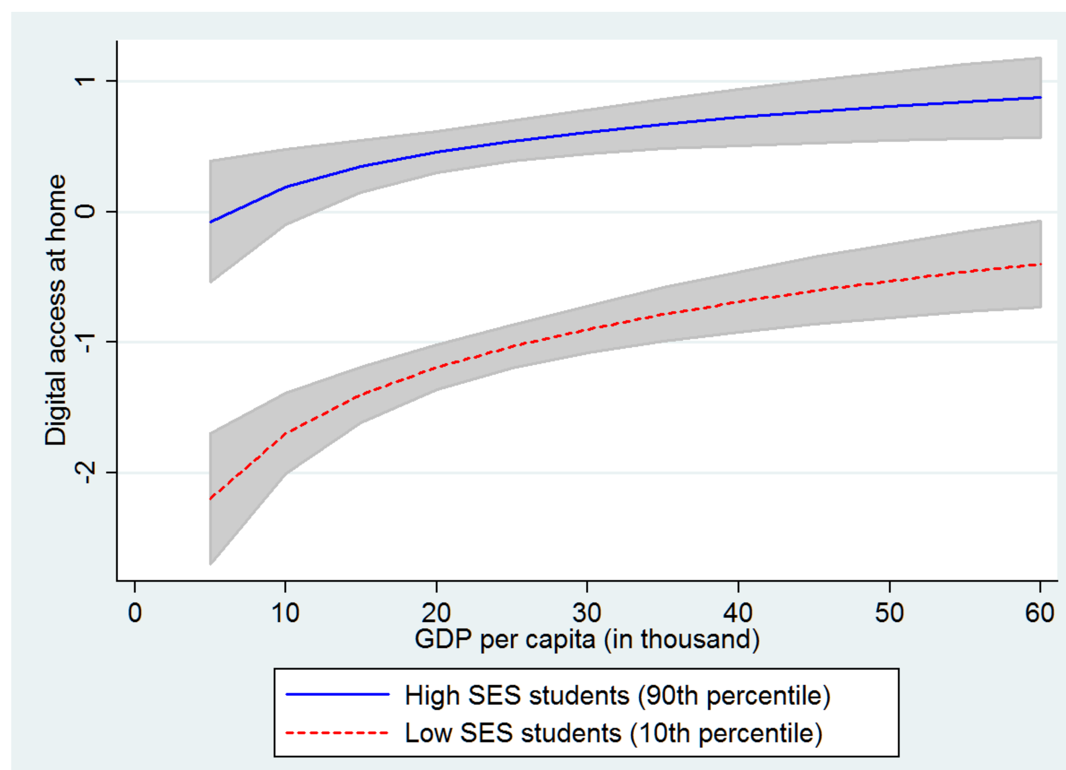


Fig 1. Predicted Digital Access at Home, Adjusted by GDP per Capita

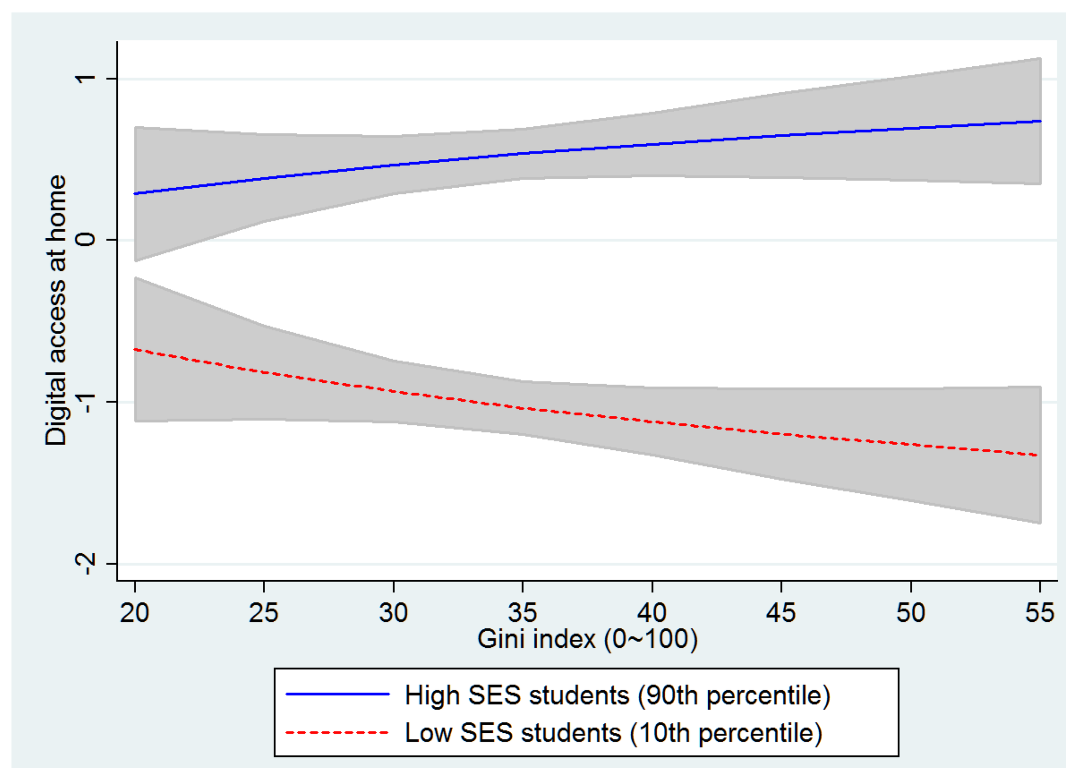


Fig 2. Predicted Digital Access at Home, Adjusted by Gini index

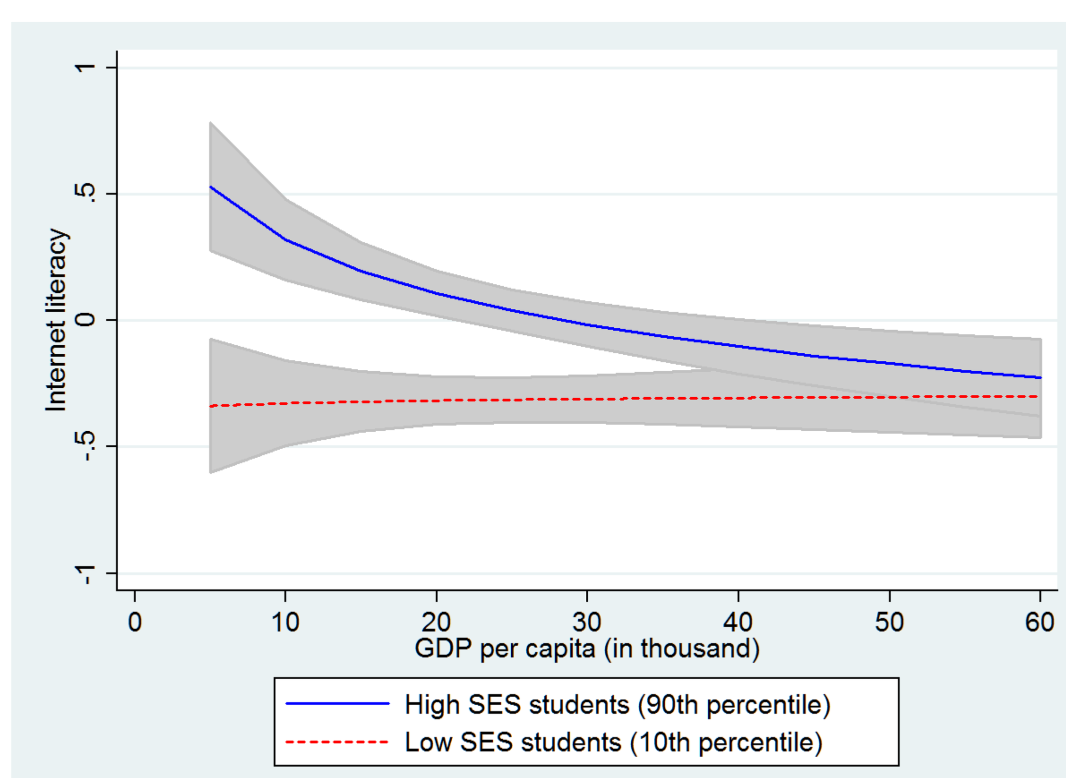


Fig 3. Predicted Internet Literacy, Adjusted by GDP per capita

DISCUSSION

The need to account for one's economic and social status in the digital divide

- Parental SES outweigh other individual background characteristics

The dynamic and the process of technological diffusion differ by a country's stage of economic growth and the level of income distribution.

- SES → Digital access at home (weaker in high income countries, stronger in more unequal countries)
- SES → Internet literacy (weaker in high income countries)

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Does Economic Growth Benefit Internet Use?

Comparing Students' Digital Access and Internet Literacy across 41 Countries[*]

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ABSTRACT

Previous literature has documented the association between parental SES and the way students utilize digital technologies: high SES students compared to their low SES counterparts have more digital skills and are more likely to use digital technologies for capital enhancing purposes. While these accounts are mainly based on single-country observations, an unexplored issue is whether this association between parental SES and student's digital use is contingent on national characteristics. In this paper, we compare 41 countries by using OECD Program for International Student Assessment (PISA) 2009. We take individual students' digital access at home and Internet literacy as two outcome variables, examining their associations with economic growth and income inequality. Our findings indicate that the socioeconomic gap in students' digital access and Internet literacy reduces by economic development and increases by income inequality. Equally important, we find that high SES students living in low income countries than in high income countries have relatively higher Internet literacy. Our paper contributes to both the digital divide literature and the education literature; we suggest that the dynamic of the digital divide and the process of technological diffusion in students' learning process are contingent on a country's stage of economic growth and income inequality.

INTRODUCTION

The recent and rapid development in digital technologies, such as computers and the Internet, has altered people's daily lives (Castells 2000). Recent literature has documented the effects of digital usage on various outcomes, such as educational performance (Attewell and Battle 1999; Attewell, Suazo-Garcia, and Battle 2003; Attewell 2001; Natriello 2001; U.S. Department of Education 2003), economic returns (DiMaggio and Bonikowski 2008), health (Baker L et al. 2003; Pew Internet and American Life Project 2013), and social relationships (Rosenfeld and Thomas 2012). Digital technologies are conceived of as a vehicle through which people—especially social-economically privileged ones— accumulate different forms of capital (DiMaggio et al. 2001, 2004). Thus, there is growing concern over the digital divide, that is: whether the access and use of digital technologies varies by one's SES and other socio-demographic characteristics.

The use of digital technologies are particularly prevalent for the age group between 15 and 30 years (Drori 2006; Hargittai and Hinnant 2008). To date, researchers are more concerned with the role of computer and Internet use in students' learning process (e.g., Attewell and Battle 1999; Attewell 2001, 2003; Natriello 2001). They suggest that the extent to which technologies benefit students' learning depends on the ways and types of digital use (e.g., use for gaming, social networking, or knowledge and information enhancement), which are largely associated with family's socioeconomic status and parental involvement (Attewell 2001, 2003; Hargittai and Hinnant 2008). However, these accounts, mostly derived from single-country observations, do not consider cross-national variation, explaining how the socioeconomic divide in students' experiences with technologies differs between countries.

To partially fill this gap, we conduct a cross-national comparison by analyzing the OECD Program for International Student Assessment (PISA) data in 2009. Previous literature on the global digital divide has clearly pointed out economic factors as an important predictor on technology diffusion both at the country-level (i.e., economic development between countries, see Drori 2010; Guillen and Suarez 2005; Hargittai 1999; Norris 2001; Robison and Crenshaw 2010) and the individual-level (i.e., income level within society, see DiMaggio et al. 2004; Kim 2011; Martin and Robinson 2007; Rogers 1995). Our study extends their work by combining both country-level and individual-level explanations; we center on two types of economic factors—economic growth and income inequality which represent between-country and within-country inequality, respectively. We ask: 1) how do economic growth and income inequality affect students' digital access and usage, and 2) how do these factors affect differently between social-economically advantaged students than their disadvantaged counterparts? In other words, the first question addresses the direct effect of these national characteristics on students' technology use. The second question accounts for potential cross-level interaction effects, examining how the social gradients of students' technology use differ across countries.

While the global digital divide scholarship (e.g., DiMaggio et al. 2001, 2004; Drori and Jang 2003; Drori 2007, 2010; Dutton et al. 2004; Hargittai 1999; Robison and Crenshaw 2010) has not attempted to link national context with students' experiences with digital technologies and the literature on technological use in education (Attewell and Battle 1999; Attewell 2003; Livingstone and Helsper 2010; Natriello 2001; Zhong 2011) has given much less attention to cross-national differences, our approach combines these two distinct literatures. In what follows, we first highlight two outcome variables of interest, explaining how their potential importance in students' learning process. We then discuss how national wealth and income inequality determines individual students' experiences with digital technologies.

THE DIGITAL DIVIDE

The Inequality of Digital Access at Home

An important research agenda is to address the location of use; that is, where to access to computers and the Internet. This indicates the degree of autonomy that users may possess without interfering by the actions of other members or the speed and time restrictions to surf online (e.g., DiMaggio et al. 2004; Hargittai and Hinnant 2008). Some scholars center on the number of locations that users are likely to access (Hassani 2006; Livingstone and Helsper 2010). Others note the importance of home access. Kim (2011) suggests that home online users compared to outside-home users are more likely to become continuing users, instead of "online dropouts." Hargittai and Hinnant (2008:606) explain that "home access can be considered the most autonomous, especially when coupled with high-speed Internet connection that allows quick access of Web sites, many of which increasingly rely on resource-intensive presentations such as animated graphics or video."

Scholars also note the potential importance of home computers and the Internet on students' academic outcomes. First, some research presents the positive effects of computer use at home on children's test scores, specifically for boys, whites, and those from higher class families (Attewell and Battle 1999). Helsper and Livingstone (2007) find that children and youth in the United Kingdom had more years of online experience and used it more frequently when they had access to the Internet at home. A cross-national study, by Zhong (2011), suggests that home digital access is crucial in predicting adolescents' self-reported digital skills and digital self-efficacy, even if countries have high Internet penetration rates. Secondly, studies show that economically disadvantaged students, especially those without Internet access at home, use school computers more frequently than their advantaged counterparts (Attewell 2001, 2003; Parsad and Jones 2005). But whether school computers benefit those poor children is questionable, due to the fact that schools that serve poor and minority students are often lack of resources to upgrade computers or to hire enough teachers with hands-on computing experiences (Attewell 2003; Natriello 2001). All of the aforementioned literature implies that digital access at home may play a crucial part in students' learning process. The first part of our study focuses on how the variance in students' digital access at home is accounted by both individual-level characteristics and national context.

Socioeconomic Divide in Digital Use

Family income and parental education outweigh other background characteristics (e.g., race, gender) in predicting the division between digital haves and have-nots (Attewell 2003). More importantly, students among socio-economic families use digital technologies in different ways. Researchers suggest that those who are well educated or socially advantaged use the Internet for more "capital-enhancing" purposes (Hargittai and Hinnant 2008; Hargittai 2010; Healy 1998). Students from poor and socially-disadvantaged families compared to those from privileged families use computers more frequently for gaming or drill and practice (Attewell 2003; Natriello 2001). Parental involvement may largely account for this difference, that "more affluent and higher educated parents are better able to provide such an environment by helping with home computing and are more likely to be aware of the importance of engaging in learning with their children (Attewell and Battle 1999:9)." Based on Attewell (2003), with more parental encouragement and supervision, students are more likely to use computers for educational purposes, that "an adult sits alongside a child at the machine, discussing what the child is doing (11)."

Therefore, students' experiences with digital technologies may differ between those from higher SES families vis-à-vis lower SES ones. The second part of our study centers on Internet literacy which accounts for the variation in the ways students use the Internet. Internet literacy refers to students' online reading habits, indicating how often they use digital technologies as an instrument for capital-enhancing purposes, such as searching for useful information and knowledge as well as extending their social networks. Livingstone and

Helsper (2009:311) define Internet literacy as "a multidimensional construct that encompasses the abilities to access, analyze, evaluate and create online content." Internet literacy is often measured by the number of activities that people do online (e.g., find useful information, read web news, use online social or for networking, see Livingstone and Helsper 2010; Sautter, Tippett, and Morgan 2010). A dimension of Internet literacy involves users' overall comprehensive and evaluations skills. These skills are inherently possessed by "digital natives" (Palfrey and Gasser 2008:167)[1] and are positively associated with school grades (Leung and Lee 2012). Internet literacy may also contain a long-term effect on students' future outcomes, as online users use new technologies for work and education (van Dijk 2005; Drori 2006; Hargittai and Hinnant 2008) and are able "to efficiently and effectively find information and the Web" without frustration and confusion (Hargittai 2002:2–3). Therefore, the second part of our study focuses the determinants of Internet literacy potentially explained by both individual-level characteristics and national context. In what follows, we discuss potential explanations on how national wealth and income inequality are associated with individual students' digital use.

CROSS-NATIONAL VARIATION IN COMPUTERS AND INTERNET USE

Economic Development: Direct Effect

Previous literature has documented the positive relationship between a country's wealth and its internet penetration rate (Guillen and Suarez 2005; Hargittai 1999; Norris 2001). Hargittai's (1999) study of 18 OECD countries shows that the economic wealth is one of the most important predictors of internet connectivity. Norris presents similar results that the magnitude of the effect of economic factor on internet access outweighs other indicators, such as educational expenditure and democracy. He shows that the rate of internet access expands exponentially once a country's Gross National Product reaches $ 9,000 per capita

[1] Digital natives, based on Palfrey and Gasser (2008), refers to the younger generation born after 1980 who adopt to new digital technologies quickly.

(Norris 2001:55). Another study of over 100 countries, by Guillen and Suarez (2005), also demonstrates that a nation's average income status has the largest effect on internet penetration rate.

Economic development determines individual students' experiences with digital technologies in three ways. First, economic development raises individuals' average income and education. People from wealthier countries spend relatively less money on necessities (e.g., food and housing) and are more likely to afford digital technologies in their lives. Also, economic growth, accompanied by the process of industrialization or post-industrialization, indicates the increased need of high-skilled and professional labor which stimulates educational expansion (Dutton et al. 2004). Based on this account, we predict that economic development promotes students' digital access at home and Internet literacy, which is largely accounted by the increase of parental SES. Also, we have shown that parents with different SES have different parenting styles and strategies (Attewell and Battle 1999; Attewell 2003). If economic development raises a country's average parental SES, we may foresee that parents from high-income countries engage more in parenting and invest more resources on children's online learning as their socioeconomic status is relatively higher than parents from low-income countries.

Secondly, economic development may have a direct effect on individual students' experiences of ICTs, net of parental SES and other individual-level characteristics. We propose the development perspective, arguing if the increased national income status lead the government to invest in research and technological development (R&D), which in turn stimulates the need of digital technology diffusion (Norris 2001:63). Some developing countries (e.g., India, Israel, Taiwan) create new economic sectors of Information and Communication Technologies (ICTs), which requires the adjustments in ICT infrastructure and the supply of high-skilled labor (Drori 2010). Economic development may also foster the competition among internet providers to provide better broadband services (Dutton et al. 2004) and to reduce the price of Internet service (Hilbert 2010).

Thirdly, we propose the public resource perspective, arguing that richer countries have more resources in public expenditure and social welfare. This causes a direct effect on students' learning process with the increased educational expenditure (Chiu 2010) or an indirect effect with the increased expenses on other social institutions, such as child health care and local communities (UNICEF 2001). Therefore, economic development may promote students' computerized and Internet skills by investing in digital technologies at public facilities such as schools, libraries, and community centers. This is especially beneficial to disadvantaged students without digital access at home. Combining the aforementioned development perspective with the public resource perspective, we predict that national wealth is positively associated with students' digital access at home and digital literacy, and these contextual effects remain once parental SES and other individual-level characteristics are taken into account.

Economic Development: Cross-National Interaction Effect

Does the increased economic development reduce the digital gap between socially advantaged students and socially disadvantaged students? Building on the development perspective, the increased national wealth benefits socially disadvantaged ones by improving their quality of life and reducing their relative expense of the basic necessities. As economic growth promotes the investment in ICT infrastructure and enhance the overall quality of Internet service, families with low income level are more able to afford computers and Internet connections and acknowledge that the adoption of new technologies could change their lives. Following this rationale, we predict that the socioeconomic divide in home digital access reduces by economic growth.

Does the increased economic development reduce the socioeconomic gap of Internet literacy? Following the public resource perspective, the increased governmental expenditure on schooling as well as other social welfare is more beneficial to socially disadvantaged students than their advantaged counterparts. This, as a compensation effect, helps students without home digital access to utilize new digital technologies in other locations such as schools, libraries, and community centers. We thus predict that the socioeconomic gradients of Internet literacy reduce by economic development, because the increased national wealth greatly benefits socially disadvantaged students from low SES families.

Does the increased national income necessarily reduce the inequality of Internet literacy, as suggested by the aforementioned public resource perspective? Consider another possibility: Public expenditures on digital technologies and Internet infrastructure and other social welfare are scarce in poor countries; this may further exacerbate the digital gap which results from the inequality of digital access at home. In other words, students' learning process as well as their experiences with digital technologies is fully contingent on their family backgrounds as they are unlikely to utilize public resources. In addition, due to its poor economic structure, people in low-income countries have fewer chances of social mobility. In order for elite students to maintain their relative social status boundary derived from their family of origin, acquiring digital skills become specifically essential to accumulate different forms of capital (DiMaggio and Cohen 2005; DiMaggio et al. 2004). On the contrary, socially advantaged students from wealthier countries may not necessary perceive digital use as the only means for capital-enhancing purposes, because in their society there are a bunch of "offline resources" for the learning (e.g., more books in the library, better schools). To consider this possibility—we term this as the resource competition model—we may see that socially advantaged students from poor countries have higher Internet literacy compared to those from rich countries.

Income Inequality: Direct Effect

We now turn to examine how income inequality affects students' digital use, net of national wealth. In highly unequal society, social mobility is almost unlikely (Wilkinson and Pickett 2009) and the rate of new technological dissemination is slow. Based on diffusion theory, the diffusion of new technologies follows an S-shaped pattern (DiMaggio et al. 2001, 2004; Martin and Robinson 2007; Rogers 1995). Take internet diffusion as an example: at first, only a small percent of the population—mainly those who are privileged—has internet access; then a growing number of middle- and working-class people start adopting the internet. The rate of growth continues to increase for a period and then gradually decreases, until finally, diffusion reaches a saturation point, leaving the remaining population—the poorest citizens—without internet access. Martin and Robinson (2007) compare this S-shaped diffusion process between the U.S. versus several European countries and find that the effect of personal income on internet use is stronger in the U.S. This may be due to the more unequal distribution of income in America compared to most Western European societies. Taken together, as new technologies gradually spread from wealthier populations to their less wealthy counterparts, the rate and extent of diffusion may depend upon the initial level of stratification within society. We predict that income inequality may impede the process of technological diffusion.

Furthermore, considering the resource distribution explanation, inequality greatly affects socially disadvantaged students as educational resources distribute unequally across schools, which increase the variation in student achievement (Chiu 2010; Gamoran and Long 2006). Wilkinson and Pickett (2009) also point out the importance of government investments in educational programs for disadvantaged students. Disadvantaged students who receive additional educational program from the government are less likely to have delinquent behaviors as in their later life stages. Equally important, drawing from the social psychological perspective, inequality deteriorates not only the disadvantaged but also students from affluent backgrounds. Wilkinson and Pickett suggest that people in unequal countries feel more anxious and insecure, as they perceive a sharp contradiction and competition among different social demographic background groups. Inequality makes disadvantaged ones feel desperate and helpless when comparing themselves to others; similarly, middle SES and high SES ones feel a great deal of insecurity when trying to maintain their current social-economic statuses, worrying about their positions will be replaced. Wilkinson and Pickett further point out that these feelings of anxiety and insecurity affect the parent-child relationship to the extent that parents feel less attached to their children, which explains how the increased income inequality decrease students' school achievement. Combining the above resource distribution explanation with the social psychological perspective, we argue that income inequality not only deteriorates students' academic and non-academic outcomes but also prevent them from acquiring digital skills. Following this rationale, we predict that income inequality is negatively associated Internet literacy and this relationship is independent from the effect of national wealth.

Income Inequality: Cross-National Interaction Effect

Does the decreased inequality within a country reduce the digital gap between socially advantaged students and their socially disadvantaged counterparts? We now turn to consider the cross-national variation in the social gradients of digital access and usage. Following diffusion theory, the effect of parental SES on home digital access is magnified in unequal countries, as the speed of technical adoption for socially-disadvantaged individuals is slower compared to that in equal countries.

Also, following the rationale from the resource distribution explanation, socially disadvantaged students' Internet skills could be greatly enhanced in equal countries where the distribution of resources is more equal. They can access Internet at schools or other public facilities (e.g., libraries) to compensate their lack of educational resources at home. Based on this explanation, we should see that the decreased income-inequality weakens the effects of digital access at home and parental SES on students' Internet literacy.

On the contrary, based on the social psychological perspective, inequality affects equivalently both high SES individuals and low SES individuals to the extent that people living in unequal countries feel more stressful and insecure. This suggests that income inequality is harmful to both socially advantaged and disadvantaged students to the extent that their overall performance, including digital skills, reduces. Following this rationale, we predict that the decreased income-inequality does not weaken the effects of digital access at home and parental SES on students' Internet literacy.

DATA, MEASURES, AND METHODS

Data

This study uses the OECD Program for International Student Assessments (PISA) 2009 data. PISA, a repeated cross-sectional survey which examines 15-year-old students' general skills and competencies with respect to their real-life situations (Werfhorst and Mijs 2010). PISA has three strengths for the purpose of my study. 1) PISA assesses students' knowledge and skills pertinent to their familiarity with digital access and usage at home. Item Response Theory (IRT) is utilized to measure these scales. IRT reduces the non-observed bias caused by guessing or incorrect responses and considers that each item has different response difficulty. 2) Students aged 15 are ideal subjects because they are very close to transitioning to colleges and to career pursuit. 3) The timing of data collection coincides with a period of increased utilization of the internet. Equally important, PISA consists of a great deal of less industrialized countries which have been seeking to keep pace. After eliminating missing cases in dependent variables and key independent variables (parental SES), my analytic sample consists of 348,794 respondents across 41 countries. To preserve cases, I utilize multiple imputations (m=1) for missing values in the control variables.

Dependent Variables

Two dependent variables are analyzed. The first one, *digital access at home*, is a composite continuous scale based on whether there is 1) educational software or 2) internet access at home and 3) how many computers are at home. Each of these three items may be influential in students' learning processes. For example, educational software provides additional educational resources; students whose families have more computers are likely to use computers for a greater variety of tasks; and, with internet access, students can communicate with teachers or search for useful information online. These three items are combined by using IRT; weighted likelihood estimates (WLE) are used to measure reliability. This variable is standardized with an OECD mean of 0 and an OECD standard deviation of 1 (OECD 2012). A positive score indicates that respondents are more likely to access different digital devices at home.

The second dependent variable, *Internet literacy*, is a composite continuous scale based on seven items: using an online dictionary or encyclopedia, searching online information to learn about a particular topic, searching for practical information online, taking part in online group discussion or forums, reading online news, reading emails, and chat online. Each of these seven items represents a different form of online reading habit and associated skill, indicating how students are familiar with reading text on the screen, sharing information and exchanging ideas, and interacting with others. Students with higher digital literacy have a better sense of where to find useful resources online for problem solving. As with the first dependent variable, these items are also combined by using IRT. The variable is standardized with an OECD mean of 0 and an OECD standard deviation of 1. Appendix 1 reports the detailed descriptions of all individual-level and country-level variables. Appendix 2 lists the descriptive statistics by country.

Individual-Level Variables

Parent SES is the key independent variable. It is a composite continuous scale based on a variety of items considering a family's economic, social, and cultural status. The items are combined by using IRT. The variable is standardized with an OECD mean of 0 and an OECD standard deviation of 1. In addition to parental SES, I include four individual-level control variables. *Gender* controls the potential digital gap between males and females. *Family structure* considers the different experiences of students living in single-parent families compared to those living in two-parent families. *Immigration* controls for minority students (foreign born) that may be disadvantaged compared to native students. Finally, *community* measures the difference between students living in rural versus metropolitan areas.

Country-Level Variables

Gross Domestic Product (GDP) per capital, in U.S. dollars (World Bank 2011), measures a country's economic standing. I take a three year moving average between 2007 and 2009. *The Gini index*, compiled by UNU-WIDER (2008) World Income Inequality Database, is used to measure income inequality. It ranges from 0 to 100, with 0 representing perfect equality; 100 perfect inequality. I take a three year moving average between 2004 and 2006.

Analytical Strategies and Statistical Methods

We use hierarchical linear models (HLM) to analyze cluster variables at the country-level (Raudenbush and Bryk 2002). HLM deals with the problems of underestimation of the standard errors or unobserved heterogeneity due to the dependence across observations from the same cluster. Two-level HLM, with individual background characteristics (level 1) and country-level cluster variables (level 2). Random intercept models are used to measure the direct effects of cluster variables; random slope models are used to measure cross-level interactions between individual-level and country-level (Rabe-Hesketh, Skrondal, and Skrondal 2008). To consider potential selection bias at the cluster level, I use Cook's distance to diagnose the potential influence of data points (Snijders and Bosker 2012).

RESULTS

The Difference of Student Sociodemographic Characteristics

We first examine how students' background characteristics are associated with the use of digital technologies. Table 1 presents the effects of individual students' background characteristics on digital access at home and Internet literacy. By using random intercept models, we allow the intercepts to randomly vary across countries. That is, unexplained variance (i.e., the remained variance which cannot be accounted by independent variables in models) is decomposed into two portions—one at the individual-level ("*sigma*") and the other one at the country-level ("*var* (*Intercept*)"). Inter-class correlation (*ICC*) calculates the ratio of the country-level variance to the total variance. It shows the percentage of unexplained variance in the dependent variable of interest that is between countries. ICC for an empty model (i.e., a model without any predictors, not shown in the table) is .361 for digital access at home, .112 for Internet literacy. These suggest that 36 percent of the variance in accessing to computers and the Internet at home is contributed by between-country variation. Besides, 11 percent of the variance in online literacy is explained by between-country differences. Once we add individual background variables into the analysis, the numbers drop to 30 percent for digital access at home and 8 percent for Internet literacy (Model 2). In what follows, we first report the effects of selected sociodemographic characteristics without parental SES (as shown in Model 1). We then add parental SES into the analysis (Model 2).

[Table 1 about Here]

Considering what accounts for the variance of digital access at home and Internet literacy, Model 1 for both outcome variables indicates that all of the effects of sociodemographic characteristics are statistically significant ($p<0.01$). Male report more digital access at home and have higher Internet literacy than females. Students who are raised by single-parent families or other types of families, as opposed to two-parent families, are more disadvantaged in accessing to digital technologies at home and acquiring online literacy. All else being equal, those who are first generation or second generation students have less digital access at home but more Internet literacy compared to native students. The effects of the location of residency indicates that students who live closer to metropolitan areas are more likely to receive advantages in digital access at home or to possess higher Internet literacy.

In Model 2, the positive effects of parental SES on students' experiences with technology use are clear and are significant (p<0.01). Comparing the change of coefficients determining digital access at home between Model 2 and Model 1, results show that once parental SES is included, the magnitude of the effects of other aforementioned sociodemographic variables on digital access at home are reduced more than a half (e.g., compare the change of male coefficients from .061 to .022) but remain statistically significant (p<0.01), with the exception of the coefficients for being second generation students (-.238 vis-à-vis .064). Also, we find similar patterns for Internet literacy in terms of how parental SES pulls down the effect sizes of other variables, with the exception that the disadvantage of living in single-parent families no longer exists (b=.005, p>0.1) and the magnitude of the effects of first generation or second generation becomes larger (0.035 to .176 and .035 to .208, respectively).

While Table 1 presents that all the individual-level factors predict the access to and the use of computers and the Internet, parental SES outweighs other selected socio-demographic background characteristics. As we can see, for example, the unexplained variance (*sigma*) for an empty model (not shown in the table) is 1.011when digital access at home is taken as the dependent variable. It decreases by 5% ((1.011–.958)/1.011) when adding a bunch of predictors (Model 1) and decreases by 27% ((.958–.701)/.958) when adding one more predictor—parental SES—into the analysis (Model 2). The same result is revealed when doing the same calculations for another dependent variable—Internet literacy. This finding is similar to what previous literature has suggested (Attewell 2003). This leads us to believe that parental SES plays a crucial role in accounting for students' daily-life experiences with digital technologies. Therefore, it is important to address if the increased economic development or the reduced income inequality could the inequality of digital technologies between higher SES students and lower SES students.

Cross-National Differences in Digital Access at Home

The former section has shown socioeconomic status at the individual-level (i.e., parental SES) as an important predictor. In this and the following section, we turn to focus on economic explanations at the country-level. Specifically, we examine how a country's GDP per capita (as a measure of economic development) and Gini index (as a measure of income inequality) affect individual students' experiences with digital use. Considering home digital access as the outcome variable, Table 2 presents individual- and country-level effects on digital access at home. We first address the direct effects of GDP per capita and the Gini index on individual students' digital access (Model 1 to Model 5), using random intercept modeling which allows the intercept to randomly vary by country. We then account for cross-level interaction effects, showing how economic development as well as income inequality at the country-level affects the slope of parental SES at the individual-level. Note that we take both GDP per capita and the Gini index as log to account for potential diminishing returns effects. Since all of the individual-level factors have been thoroughly discussed in the former section, we do not report their coefficients and standard errors to simplify the table.[2]

Direct Effect. Model 1 and Model 3 display the bivariate associations, presenting how GDP per capita or the Gini index, respectively, is associated with digital access at home.

[2] In contrast to results from Table 1, the coefficients of individual-level variables do not greatly change when adding country-level variables in the models.

Results clearly indicate that both GDP per capita and the Gini index are associated with individual students' digital access at home and this association is nonlinear (p<0.01). The nonlinear effect of GDP per capita reveals that among low-income countries, home digital access increases rapidly during the early stage of economic growth. But as a country's economic status continuously increases, the positive effects of GDP per capita become weaker; the rate of improvement slows down among middle-income countries and eventually disappears among high-income countries. Considering the nonlinear effect of the Gini index, as a country becomes more unequal, students likely have less access to computers and the Internet at home. But this negative association becomes weaker as the income inequality continually rises and, finally, disappears among high-inequality countries.

Furthermore, these associations remain statistically significant once we control for individual-level characteristics (p<.01 for *GDP in Model 2* ; (p<.05 for *Gini in Model 4*). It is noted that the effect size decreases once we add individual-level factors into models. For GDP per capita, the coefficient decreases by 42 percent (Model 1 versus Model 2: (0.903–0.521)/0.903); regarding the Gini index, its coefficient drops by 51 percent (Model 3 versus Model 4: (–1.511+0.733)/ –1.511). This reflects the notion that economic development raises a country's average educational level and income, due to the increased need of high-skilled and professional labor (Dutton et al. 2004).

How large is the effect of economic development and income inequality on students' digital use? Comparing unexplained variance for an empty model (*var* (*Intercept*) = .571, not shown in the table) with Model 1 or with Model 3, respectively, we find that GDP per capita explains 56 percent of the country-level differences ((.571–.254)/.571). The number for the Gini index is 23 percent ((.571–.437)/.571). This finding, that GDP per capita is a key one explaining cross-national differences, is consistent with previous literature which suggests that economic factors are critical in shaping technology diffusion (Drori 2006; Hargittai

1999:199; Norris 2001).

When taking both GDP per capita and the Gini index into the same model, as shown in Model 5, the effect of the former remains substantially important (p<0.01) but the later turns to statistically insignificant (p>0.1). This suggests that economic development outweighs income inequality.

Cross-Level Interaction Effect. To examine if the dynamic of parental SES impact on students' experiences with digital use may differ across nations, we utilize random slope modeling to let the slope of parental SES randomly vary among countries. When accounting for the random effect of parental SES (*var* (*Parent SES*)), Model 5 suggests that the slopes for each country range between .430 and .582 (.506±(1.960×.039), α=.05). The next step, then, is to examine what country-level factors could explain this variance. In Model 6, we add two cross-level interaction effects, addressing if the magnitude of the effect of parental SES on students' digital access at home depends on economic development and income inequality. Results clearly show that the effect of parent SES within a country decreases by GDP per capita (b=-0.114, p<0.01) but increases by the Gini index (b=0.362, p<0.01).

In order to further explain the substantive meaning of these cross-level interactions, I calculate the predicted value of digital access at home between students from high SES families (the top 10 percent) versus low SES families (the bottom 10 percent), based on Model 6. As shown in the left panel of Figure 1, the effect of GDP per capital differs by students from a variety of socio-economic status categories. For example, moving from low income countries (GDP per capita = 10,000 USD) to high income countries (GDP per capita = 50,000 USD), the likelihood of digital access at home increases by 1.169 standard deviation (from -1.701 to -.532) among students from low SES families, compared to 0.618 standard deviation (from .190 to .808) among students from high SES families. Put it in another way, the graph also clearly shows us that the gap of computer and Internet access between high

SES and low SES students is reduced by economic development; the difference moves from 1.891 standard deviation (.190 –(–1.701)) among poor countries (GDP per capita = 10,000 USD) to 1.340 standard deviation (.808 –(–.532)) among high-income countries (GDP per capita = 50,000 USD). Taken together, the inequality of digital access at home is 0.551 standard deviations smaller in high-income countries compared to their low-income counterparts (1.891–1.340), due to social-economically disadvantaged students receive more benefit from economic development.

[Figure 1 about Here]

The right panel of Figure 1 predicts the effect of the Gini index on home digital access. The graph clearly shows the increased income inequality pulls down the likelihood of those from low SES families to acquire computers and the Internet at home; on the contrary, the increased income inequality does not reduce but slightly raise the likelihood to use digital technologies at home for those from high SES families. The gap between high SES students and their low SES counterparts in more equal countries (Gini index = 0.30) is 1.399 standard deviation (.467– (–.932)), compared to 1.847 standard deviation (.650– (–1.197)) in more unequal countries (Gini index = 0.45). To sum up, we can see that the increased Gini index dramatically widens the inequality of home digital access between students from a various SES families.

Cross-National Differences in Internet Literacy

We now center on the variance of the way how Internet is utilized. Table 3 reports individual- and country-level effects on Internet literacy. The first three models account for the direct effects of GDP per capita and the Gini index on individual students' online literacy. Random intercept modeling is used to allow the intercept to randomly vary by country. To avoid potential selection bias, that one's digital skills may depend on whether s/he has the access to digital technologies, we control for the effect of digital access at home in addition to other selected individual-level variables.

[Table 3 about Here]

Direct Effect. Model 1 and Model 2 reports the bivariate relationships. As expected, Internet literacy is positively associated with the log of GDP per capita (Model 1) and negatively associated with the Gini index (Model 2). Considering unexplained variance for an empty model (*var* (*Intercept*) = .141, not shown in the table) with Model 1 or with Model 2, respectively, we find that GDP per capita explains 33 percent of the country-level differences ((.141–.009)/.141) and the Gini index explains 18 percent ((.141–.012)/.141).

After we control for individual-level variables, as shown in Model 3, the effect of GDP per capita turns to negative and is statistically significant (p<0.1), whereas the effect of the Gini index becomes statistically insignificant (p>0.1). This indicates that individual background characteristics play an important role in determining online reading habits and skills. However, how can we explain the unexpected finding, that GDP per capita is negatively associated with Internet literacy, net of individual-level factors and Gini coefficient? One possibility is to look at cross-level interaction effects.

Cross-Level Interaction Effect. Model 4 shows that the effect of parent SES becomes larger as a country's Gini index increases (p<0.01), but this interaction become statistically insignificant (p>0.1, see Model 5) once we add the cross level interaction between the log of GDP per capita and parent SES. As shown in Model 5, the magnitude of the effect of parent SES decreases as a country's GDP per capita increases (b=- 0.130, p<0.01). Taken together, the increased economic development reduces the inequality of Internet literacy resulted from different SES. Moreover, both GDP per capita and the Gini index can explain 50 percent of the country-level difference in parental SES slope (*var* (*Parent SES*) = .014 in Model 3, *var* (*Parent SES*) = .007 in Model 5), but economic factor outweighs income inequality.

In order to further explain the substantive meaning of these cross-level interactions, I calculate the predicted change of Internet literacy between students from high SES families versus from low SES families, based on Model 5 in Table 3. As shown in Figure 2, the effect of GDP per capita differs by class. For instance, when moving from low income countries (GDP per capita = 10,000 USD) to high income countries (GDP per capita = 50,000USD), predicted online literacy almost does not change and slightly increases by 0.025 standard deviations (–.302– (–.327)) among students from low SES families. Among students from high SES families, on the contrary, moving from low income countries to high income countries reduces online literacy by 0.490 standard deviations (–.170– (.320)).

[Figure 2 about Here]

Equally important, the gap of online reading by SES reduces as GDP per capita increases. When a country's GDP per capita is close to 40,000 USD, the confidence intervals (as shown in grey areas) for the two predicted lines overlap. This suggests that the gap between high SES students and low SES students greatly reduces by economic development and eventually diminishes among high income countries. Note that in this figure all the remaining variables are controlled, including the effects of individual background characteristics and the Gini coefficient. Taken together, we can see that the increased economic development reduce the Internet literacy gap between students from a various SES families.

DISCUSSION

The adoption of digital technologies is prevalent for younger generation. Previous research has documented the effect of technologies in students' learning process (e.g., Attewell and Battle 1999; Attewell et al. 2003). Whether technologies could be beneficial to students' well-beings are contingent upon family background and the ways computers and the Internet are utilized (Attewell 2001; Hargittai 2002). While most of these accounts are mainly based on single-country observations, this study centers on what account for cross-national variations in middle school students' digital use and why the socioeconomic gap in digital divide is larger in some countries than others.

We argue that the dynamic and the process of technological diffusion differ by a country's stage of economic growth and the extent of income distribution. The former compares average income difference between countries and the latter considers the level of stratification within a society. We examine how these two national characteristics affect individual students' digital access and the way how they use the Internet. Equally important, we address whether the digital divide between higher class students and their lower class counterparts reduces as a country's economy enhances or its income inequality reduces.

We utilize the data derived from the Program for International Student Assessment (PISA) in 2009. By using hierarchical level modeling, we consider both individual-level factors and country-level factors into the analysis. Considering individual-level accounts, we present that while students' background characteristics predict their digital access at home and Internet literacy, the magnitude of the effect of parental SES outweigh other factors (e.g., gender, family structure, immigrant status, and school location). This suggests the importance of one's economic and social status in the technology divide. Although this pattern is similar across countries, we further shows that the socioeconomic gap in students' digital use is reduced as economic development goes up but exacerbates as a country becomes more unequal. Moreover, economic development also weakens the gap of Internet literacy between high SES students and low SES students. More importantly, we find that economically and socially advantaged students in low income countries have higher online literacy compared to those in high income countries. For disadvantaged students, on the contrary, the increased economic development does not necessarily enhance their Internet skills.

Lastly, our findings suggest 1) a positive effect of GDP per capita on individual students' digital access at home, net of individual background characteristics, 2) a direct effect of economic development on students' digital access, and 3) an indirect effect of economic development on students' Internet literacy and skills through students' socio-demographic status. 4) Once we control for students' individual-level characteristics, the effect of economic development becomes negative. A summation of the above offers us new sociological insights: first, reflecting Attewell's (2001, 2003) account which centers on how parenting affect students' technology use, we suspect that higher class parents—the elites—in poorer countries compared to those in richer countries are more likely to perform their parenting and concern in shaping children's digital use experience. Secondly, we present another potential explanation: in poor countries where public expenditure in education and Internet infrastructure is scarce and social welfare is limited, higher SES students mostly rely on the Internet to access different forms of information. In contrast, higher SES students among rich countries are privileged to utilize more "offline resources" (e.g., higher amount of school investment, better libraries) as part of their learning process. Thus, they are more likely to use the Internet for non capital-enhancing purposes.

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Table 1. The Effects of Students' Background Characteristics on Digital Access at Home and Internet Literacy

	Digital access at home		*Internet literacy*	
	Model 1	Model 2	Model 1	Model 2
Male	0.061**	0.022**	0.053**	0.032**
	(0.003)	(0.003)	(0.004)	(0.003)
Single-parent family	-0.283**	-0.147**	-0.072**	0.005
	(0.004)	(0.004)	(0.005)	(0.005)
Other family	-0.281**	-0.110**	-0.177**	-0.080**
	(0.009)	(0.008)	(0.010)	(0.009)
First generation	-0.281**	-0.034**	0.035**	0.176**
	(0.009)	(0.007)	(0.009)	(0.009)
Second generation	-0.238**	0.064**	0.035**	0.208**
	(0.008)	(0.007)	(0.009)	(0.009)
Village	-0.377**	-0.123**	-0.416**	-0.271**
	(0.007)	(0.006)	(0.007)	(0.007)
Small town	-0.163**	-0.042**	-0.147**	-0.078**
	(0.005)	(0.004)	(0.005)	(0.005)
City	0.207**	0.065**	0.160**	0.079**
	(0.005)	(0.004)	(0.005)	(0.005)
Large city	0.375**	0.155**	0.268**	0.142**
	(0.006)	(0.006)	(0.007)	(0.007)
Parent SES		0.534**		0.305**
		(0.001)		(0.002)
Intercept	-0.191	-0.131	-0.125*	-0.091+
	(0.122)	(0.086)	(0.059)	(0.047)
var (*Intercept*)	0.592	0.297	0.141	0.089
sigma	0.958	0.701	1.087	1.003
ICC [a]	0.382	0.298	0.115	0.082

Data Source. PISA, 2009.

Notes. N = 348,794 (41 countries). Standard errors are in parentheses. All coefficients are adjusted by multiple imputations for missing cases in controls (m = 1). Female, Two-parent family, Native, and Town are reference categories. [a] ICC for an empty model: 0.361 when y = Digital access at home; 0.112 when y = Internet literacy.

+ p < .1, * p < .05, ** p < .01 (2-*tailed*).

Table 2. The Effects of Economic Development and Income Inequality on Digital Access at Home

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Individual level factors:						
Other control variables[a]		yes		yes	yes	yes
Parent SES		0.534**		0.534**	0.506**	0.524**
		(0.001)		(0.001)	(0.031)	(0.022)
Country-level factors:[b]						
GDP (log)	0.903**	0.521**			0.518**	0.517**
	(0.126)	(0.110)			(0.136)	(0.136)
Gini (log)			-1.511**	-0.733*	0.020	0.020
			(0.427)	(0.336)	(0.353)	(0.353)
Cross-level interactions:						
GDP (log) × *Parent SES*						-0.114**
						(0.041)
Gini (log) × *Parent SES*						0.362**
						(0.107)
Intercept	-0.225**	-0.133+	-0.287**	-0.162+	-0.076	-0.076
	(0.079)	(0.069)	(0.105)	(0.083)	(0.074)	(0.074)
var (*Intercept*)	0.254	0.193	0.437	0.266	0.208	0.208
var (*Parent SES*)					0.039	0.019
sigma	1.011	0.701	1.011	0.701	0.669	0.669
ICC[c]	0.201	0.215	0.302	0.275	0.237	0.237

Data Source. PISA, 2009.

Notes. *N* = 348,794 (41 countries). Standard errors are in parentheses. All coefficients are adjusted by multiple imputations for missing cases in controls (m = 1). [a] Other control variables include Male, Single-parent family, Other family, 1st generation, 2nd generation, Village, Small town, City, and Large city. [b] all country-level variables are grand mean centered. [c] ICC for an empty model: 0.361.

Table 3. The Effects of Economic Development and Income Inequality on Internet Literacy

	Model 1	Model 2	Model 3	Model 4	Model 5
Individual level factors:					
Other control variables[a]			yes	yes	yes
Digital access at home			0.314**	0.314**	0.314**
			(0.002)	(0.002)	(0.002)
Parent SES			0.124**	0.134**	0.126**
			(0.019)	(0.017)	(0.014)
Country-level factors:[b]					
GDP (log)	0.349**		-0.178**		-0.179**
	(0.077)		(0.064)		(0.064)
Gini (log)		-0.673**	-0.196	0.053	-0.197
		(0.219)	(0.165)	(0.151)	(0.165)
Cross-level interactions:					
GDP (log) × *Parent SES*					-0.130**
					(0.025)
Gini (log) × *Parent SES*				0.207**	0.024
				(0.070)	(0.065)
Intercept	-0.120*	-0.148**	-0.016	-0.006	-0.016
	(0.048)	(0.054)	(0.034)	(0.037)	(0.034)
var (*Intercept*)	0.094	0.115	0.045	0.054	0.045
var (*Parent SES*)			0.014	0.012	0.007
sigma	1.120	1.120	0.917	0.917	0.917
ICC[c]	0.077	0.093	0.047	0.055	0.047

Data Source. PISA, 2009.

Notes. N = 348,794 (41 countries). Standard errors are in parentheses. All coefficients are adjusted by multiple imputations for missing cases in controls (m = 1). [a] Other control variables include Male, Single-parent family, Other family, 1st generation, 2nd generation, Village, Small town, City, and Large city. [b] all country-level variables are grand mean centered. [c] ICC for an empty model:

+ $p < .1$, * $p < .05$, ** $p < .01$ (2-*tailed*).

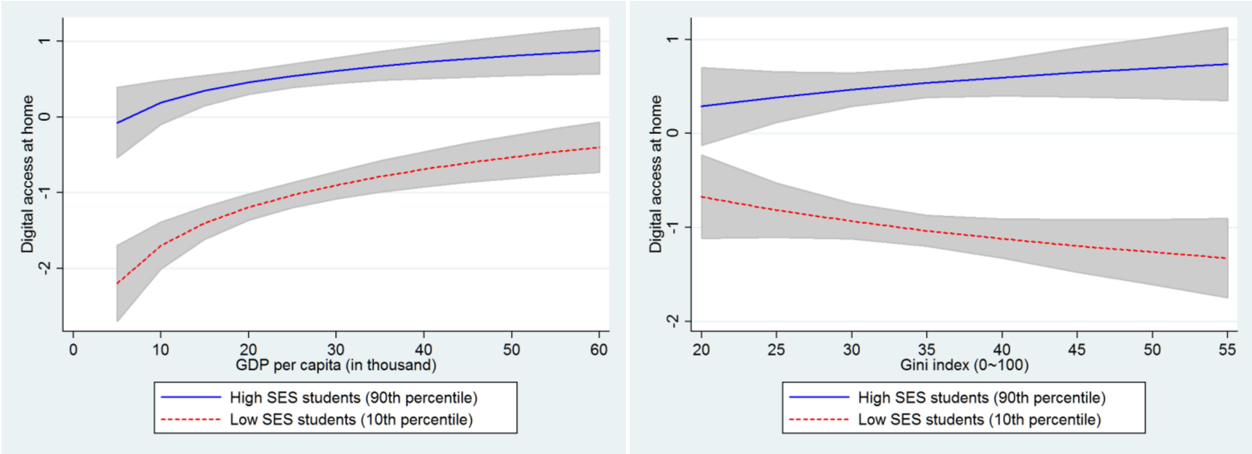

Figure 1. Predicted Digital Access at Home between High SES versus Low SES Students

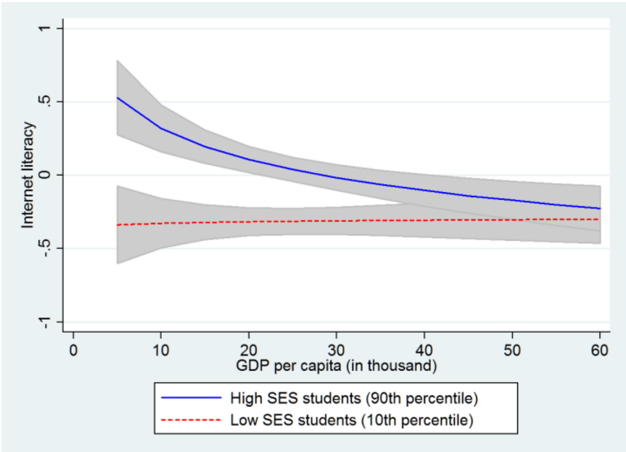

Figure 2. Predicted Internet Literacy between

High SES Students versus Low SES Students

Appendix 1. Variables List and Measures

Variable	Mean	Sd	Min	Max	Description / Coding
Individual-level variables					
Digital access at home	-0.34	1.27	-3.82	3.12	IRT scaling based on three items: "do you have educational software at home (yes or no)?", "do you have a link to the internet at home (yes or no)?", and "how many computers are there at your home (0, 1, 2, or 3 or more)?"
Online reading	-0.16	1.11	-5.35	3.51	IRT scaling based on seven items: using an online dictionary or encyclopedia (e.g., Wikipedia), searching information to learn about a particular topic, searching for practical information (e.g., schedules, events, tips, recipes), taking part in online group discussion or forums, reading online news, reading emails, and chat online. For each item, respondents chose from five response categories: I don't know what it is, never or almost never, several times a month, several times a week, and several times a day.
Parent SES	-0.25	1.14	-6.04	3.44	IRT scaling based on five indices: highest parental occupation status (HISEI), highest parental education (in years), family wealth (a room of your own, a link to the internet, a dishwasher, a DVD player, cellular phones, televisions, computers, cars, rooms with a bath or shower, and other country-specific wealth items), cultural possessions (classical literature, books of poetry, and works of art), and home educational resources (a desk to study, a quiet place to study, educational software, books to help with your school work, technical reference books, and a dictionary).
Male	0.49	0.50	0.00	1.00	1 is male; female 0.
Single-parent family	0.17	0.37	0.00	1.00	1 is single-parent family; two-parent family 0.
Other family	0.04	0.19	0.00	1.00	1 is other family; two-parent family 0.
1st generation	0.04	0.20	0.00	1.00	1 is first generation student; native student 0.
2nd generation	0.05	0.21	0.00	1.00	1 is second generation student; native student 0.
Village	0.09	0.28	0.00	1.00	1 is village; large city 0.
Small town	0.22	0.41	0.00	1.00	1 is small town; large city 0.
City	0.25	0.43	0.00	1.00	1 is town; large city 0.
Large city	0.11	0.31	0.00	1.00	1 is city; large city 0.
Country-level variables					
GDP per capita	28.59	13.66	3.85	82.75	US dollars in thousand (World Bank 2011).
GDP per capita (*ln*)	3.21	0.58	1.35	4.42	
Gini index	36.47	9.62	23.00	56.50	The distribution, in %, of income or consumption expenditure among individuals or households within a country deviating from a perfectly equal distribution. 0 is perfect equality, 100 perfect inequality (UNU-WIDER 2008).
Gini index (*ln*)	3.56	0.25	3.14	4.03	

Data Sources: UNU-WIDER, 2008. *World Income Inequality Database* , Version 2.0c, May 2008; World Bank, 2011. *World Bank Data* .

Appendix 2. Descriptive Statistics by Country

Country	Sample size	Digital access at home		Online Reading		Parent SES		GDP	Gini index
		mean	*sd*	*mean*	*sd*	*mean*	*sd*		
Albania	4596	-1.88	1.18	-0.55	1.26	-0.92	0.99	7.98	31.10
Argentina	4774	-0.72	1.37	-0.51	1.17	-0.59	1.16	14.11	49.67
Australia	14251	0.45	0.78	-0.12	0.88	0.30	0.76	37.32	29.30
Austria	6590	0.12	0.66	0.04	0.92	0.11	0.84	38.91	25.67
Belgium	8501	-0.08	0.78	-0.19	0.78	0.21	0.92	36.41	27.33
Brazil	20127	-0.93	1.24	-0.66	1.44	-1.16	1.20	10.20	56.50
Bulgaria	4507	0.22	1.33	0.29	1.46	-0.12	0.98	13.29	33.53
Canada	23207	0.27	0.82	-0.12	0.93	0.49	0.83	38.37	32.40
Chile	5669	-0.28	1.34	-0.21	1.08	-0.49	1.16	15.03	54.60
Czech Republic	6064	0.10	0.82	0.53	0.99	0.02	0.75	25.65	24.83
Denmark	5924	0.29	0.57	0.14	0.81	0.12	0.93	38.60	24.00
Finland	5810	0.07	0.63	-0.06	0.78	0.41	0.78	36.59	25.67
France	4298	-0.04	0.71	-0.12	0.88	-0.12	0.84	33.57	27.67
Germany	4979	0.23	0.65	0.03	0.92	0.14	0.88	36.10	27.00
Greece	4969	-0.32	1.07	-0.14	1.20	0.02	0.99	28.85	33.33
Hong Kong	4837	-0.22	0.95	0.37	0.91	-0.81	1.01	44.20	51.40
Hungary	4605	-0.14	0.88	0.43	1.03	-0.16	0.95	19.87	27.17
Iceland	3646	0.49	0.59	0.20	0.89	0.72	0.88	38.09	25.00
Indonesia	5136	-2.85	0.82	-1.42	1.38	-1.54	1.09	3.85	39.40
Ireland	3937	-0.06	0.86	-0.48	0.93	0.04	0.85	42.79	32.00
Israel	5761	-0.41	0.90	-0.06	1.10	-0.02	0.88	25.60	37.20
Italy	30905	-0.11	0.96	-0.07	1.17	-0.10	0.98	32.54	32.67
Japan	6088	-0.94	1.07	-0.49	0.97	-0.01	0.73	33.01	31.90
Korea	4989	-0.50	1.02	-0.20	0.84	-0.14	0.83	26.56	31.60
Latvia	4502	0.37	1.27	0.35	0.96	-0.05	0.86	17.06	38.03
Luxembourg	4622	0.29	0.63	0.02	0.95	0.22	1.09	82.75	26.67
Mexico	38250	-1.72	1.42	-0.45	1.10	-1.16	1.28	14.18	50.45
Netherlands	4760	0.55	0.55	0.12	0.75	0.32	0.85	41.54	26.50
New Zealand	4643	-0.12	0.91	-0.26	0.90	0.10	0.78	29.07	33.50
Norway	4660	0.71	0.56	0.18	0.86	0.48	0.74	57.11	27.67
Peru	5985	-2.02	1.09	-0.66	1.39	-1.27	1.22	8.39	47.60
Poland	4917	0.37	1.11	0.47	1.09	-0.22	0.91	17.85	36.60
Portugal	6298	0.76	0.86	0.14	0.90	-0.30	1.16	24.67	38.00
Romania	4776	-0.10	1.21	-0.13	1.42	-0.31	0.91	13.90	36.13
Russian Federation	5308	-0.20	1.39	-0.46	1.44	-0.15	0.80	18.63	45.50
Spain	25887	-0.33	0.85	-0.12	0.90	-0.24	1.06	32.46	31.33
Sweden	4567	0.42	0.64	0.03	0.84	0.33	0.81	38.44	23.00
Switzerland	11812	0.05	0.62	-0.03	0.88	0.02	0.86	46.52	31.10
Thailand	6225	-0.86	1.45	-0.69	1.30	-1.16	1.26	7.86	42.00
United Kingdom	12179	0.32	0.65	0.24	0.84	0.20	0.68	35.44	33.00
United States	5233	-0.10	1.03	-0.16	1.01	0.16	0.92	46.14	46.40