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The Inequality of Digital Learning among Students in Rich and Poor Countries

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ABSTRACT

The Internet has become indispensable to education throughout the world. Despite the growing importance of the Internet, a gap in digital skills and usage according to socioeconomic status—known as the digital divide or digital learning inequality—exists in many countries. Comparative research has focused mainly on the digital divide among adults, leaving it underexplored among students. And we know little about whether the use of digital technology increases or reduces existing educational inequality. My dissertation uses comparative analysis to address gaps in the literature, by examining the digital divide among 15-year-old students in a wide range of countries, using data from the 2009 wave of the Programme for International Student Assessment (PISA). I use three-level multilevel analysis to estimate school- and country-level determinants of the digital divide among students from various socioeconomic backgrounds. Findings from the dissertation make several contributions to education and stratification research. First, increased national expenditure on research, innovation, and secondary education reduce the gap in digital use that is directly related to school-related tasks (i.e., use of educational software, digital use for schoolwork at home) in both more- and less-developed countries. However, this investment in poor countries does not reduce the gap in Internet literacy between socioeconomically advantaged and disadvantaged students, but widens it. Second, although

digital use at school positively predicts digital learning, the association differs greatly between schools and across countries. For poor countries, the use of digital technology is more beneficial to students who attend socioeconomically disadvantaged schools than those in privileged schools. For rich countries, on the other hand, increasing the use of digital technology in the classroom increases the relative advantage of attending privileged schools. Third, social segregation in schools plays an important role in influencing the digital learning opportunities of students in four Chinese societies--Shanghai, Taiwan, Hong Kong, and Singapore. Specifically, Shanghai has a highest level of digital learning inequality, largely due to disparities in Internet access and more school-choice opportunities for parents. My dissertation concludes by discussing the different implications for policymakers in poor and affluent countries who want to reduce the digital divide.

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Chapter 1:

Introduction

1.1 The Role of Governments in the Promotion of Digital Learning

Digital technologies have dramatically altered our daily lives (Castells 2000; DiMaggio et al. 2001, 2004; ITU 2015; Lenhart and Pew Research Center 2015; Litt 2013; Norris 2001) and deeply penetrated many educational settings (Attewell 2001, 2003; Bradbrook et al. 2008; Hill 2010; Looker and Thiessen 2003; Selwyn, Gorard, and Williams 2001; Vigdor, Ladd, and Martinez 2014). Numerous national policies have been developed and implemented to promote digital learning in schools (Carvin, Conte, and Gilbert 2001; Culp et al. 2003; DeBell and Chapman 2006; Erichsen and Salajan 2014; Selwyn et al. 2001; Spring 2008; U.S. Department of Education 1996; Wells and Lewis 2006; White House 2013). The origins of the United States (U.S.) digital learning policy can be traced to the 1983 federal report, *A Nation at Risk*. It recognized basic computer skills as one of the "Five New Basics" that should be covered in public schools (National Commission on Excellence in Education 1983). Later, the European Union (E.U.) released the Bangemann report, which recommended that governments "extend advanced distance learning techniques into schools and colleges (European Commission 1994:29). In *Teaching and Learning: Towards the Learning Society*, the E.U. describes the forces that have propelled the need for countries to develop digitally literate populations:

> Three major, profound and wide-ranging factors of upheaval have emerged, however, which have transformed the context of economic activity and the way our societies function in a radical and lasting manner, namely: the onset of the information society; the impact of the scientific and technological world; and the internationalisation of the economy. These events are contributing towards the

development of the learning society. (European Commission 1995:5)

Driven by these impulses, the number and urgency of the national efforts to promote digital learning has grown significantly around the globe (Drori 2010; Pietrass 2007; Spring 2008; UNESCO 2000, 2015; UNESCO-UIS 2015), which inspired competition among countries trying not to fall behind in the digital revolution. In Asian countries like China, Taiwan, South Korea, and Singapore, for example, a set of policy initiatives targeted the promotion of e-literacy and digital skills in secondary and tertiary education (Chen 2007; Ministry of Education 2006; Mo et al. 2013; Zeng et al. 2012). Although studies in less-developed countries indicate a growing commitment to increasing e-literacy as well (Batchelor et al. 2003; Beuermann et al. 2013; Bhanji 2012; Carr-Chellman 2005; Cristia et al. 2012; UNESCO-UIS 2013, 2014, 2015), their abilities to support digital learning policies are more limited because of the lack of required resources and the growing global inequality in the access and use of Information and Communication Technology (ICT) (Drori 2006, 2010; UNESCO 2015).

1.2 Cross-National Variation in Digital Learning Inequality

Despite the progressive spread of digital technology and the growing importance of digital learning, several inequalities have been identified. The first disparity, referred to as the "first digital divide," concerns the inequality in access to digital technology in schools or at home (Attewell 2001:253). Recent studies have found a decline in the digital access divide in more-developed countries, which is due largely to the intentional efforts of policymakers, educators, and entrepreneurs. But the problem persists in less-developed countries (ITU 2011; Norris 2001). Figure 1.1 shows the percentage of students in 73 countries and societies who reported having a computer at home, based on the results from the 2009 Programme for International Student Assessment (PISA) data. Among all the countries and societies, student access to a computer at

home was positively associated with their socioeconomic background. However, the gap between socioeconomically advantaged (i.e., those in the top decile) versus disadvantaged students (i.e., those in the bottom decile) is larger in less-developed countries (e.g., see Mexico, Kazakhstan, and Colombia on the left) than in their more-developed counterparts (e.g., see Netherlands, Liechtenstein, and Denmark). Figure 1.2 presents a similar pattern, when comparing the relationship between students' socioeconomic background and *Internet access at home*. In both more- and less-developed countries, socioeconomically advantaged students reported higher levels of Internet access at home compared to disadvantaged students. In addition, the percentage of socioeconomically disadvantaged students having Internet access at home is positively associated with national income level—more of the poorer students have home internet access in richer countries.

[Figure 1.1 and Figure 1.2 about Here]

Unlike the first disparity, the second disparity (the "second digital divide") concerns an inequality in skills and usage for educationally productive purposes that exists even after access has been achieved (Attewell 2001; DiMaggio et al. 2004; Hargittai 2002; Natriello 2001). Although less studied than the first digital divide, the second digital divide is found to be a problem for all countries, regardless of economic development (Attewell and Battle 1999; Drori 2010; Hargittai and Hinnant 2008; ITU 2011; Kim 2008; Leu et al. 2014; Notten et al. 2009). For instance, recent studies from the U.S. (Attewell 2003; Leu et al. 2014), Australia (Smith, Skrbis, and Western 2013), and Britain (Livingstone and Helsper 2008) show that students with highly educated parents have better computer skills and are more likely to use the Internet for learning.

Related to this, an important research agenda would address how to explain cross-national variation in the digital divide. Comparative research on the global digital divide has

identified several country-level factors that affect the rate of technology diffusion (e.g., *access* to a computer and the Internet), including economic development (Guillén and Suárez 2005; Norris 2001; Robison and Crenshaw 2010), digital infrastructure development (Dutton et al. 2004), and the "democraticness" (degree of democracy practiced) of government (Corrales and Westhoff 2006; Robison and Crenshaw 2010). For instance, Hargittai (1999) shows that the rate of Internet access largely depends on a nation's wealth and its level of competition in the telecommunications sector. Norris (2001) suggests that both economic development and research and development (R&D) are the strongest predictors of Internet connectivity.

Most of these studies, while informative, focus on the adult population, thus ignoring the experiences of youth—one of the most relevant portions of the population when considering the digital divide (Robinson 2014). Moreover, little is known about the determinants of the digital learning inequality between affluent and poor students—an inequality in computer use and Internet searching skills for educational purposes that exists even after digital access has been achieved (Attewell 2001; DiMaggio et al. 2004; Hargittai and Hinnant 2008)—the more salient problem at this time.

1.3 Outline of Dissertation

In this dissertation, I compare the digital learning inequalities among 15-year-old students in a set of countries, using the 2009 wave of the PISA data collected by the Organization for Economic Cooperation and Development (OECD). By "digital learning inequalities," I mean the differences between students in having educational software at home, using a computer for schoolwork, and searching for information and seeking knowledge throughout the Internet. Broadly, the dissertation centers on three overarching research questions:

1. How do digital learning opportunities differ between students?

2. How do digital learning opportunities vary among schools?
3. What explains variation in digital learning inequality among countries?

The dissertation includes seven chapters. In this chapter, I explain the importance of cross-national comparative analysis when studying the digital learning inequality of 15-year-old students. I also describe the overarching research questions and the organization of the dissertation.

Chapter 2 provides the theoretical framework for the dissertation. Drawing from the global digital divide literature and scholarship on comparative education, I discuss individual- and school-level explanations of the digital divide. Moving up to country-level accounts, I identify the national investments that may be relevant in promoting digital learning for students from socioeconomically disadvantaged groups. Comparing the differences between rich and poor countries, I highlight the fact that social inequality and widespread poverty in less-developed countries may limit their ability to bridge the digital divide. Lastly, I address the link between digital use at school and digital learning, and examine how the relationship may differ between schools and vary across countries.

In Chapter 3, I describe the data, measures, and methods that I employ in the dissertation. The primary source of data is the OECD PISA data collected in 2009. To capture national-level indicators, I geocode a set of country-level factors from a variety of publicity available sources, mainly the World Bank's World Development Indicators database, the United Nations Educational, Scientific, and Cultural Organization (UNESCO) Institute for Statistics database, and the World Income Inequality database. I also explain the need to use a multilevel approach for the analysis of my dissertation.

In Chapters 4 and 5—the first two empirical chapters—I examine cross-national

variations in the inequalities of digital learning at the student and school levels, respectively. I outline a wide range of country-level explanations of digital learning inequality. I focus first on the economic development and political freedom of a society—the two factors that have been extensively developed in previous literature (e.g., see Norris 2001; Robison and Crenshaw 2010). Moving beyond economic and political explanations, I further explore three country-level factors that have recently received much attention in research on comparative education (Dale 2005; Erichsen and Salajan 2014; Spring 2008) and the global digital divide (Drori 2006, 2010; Dutton et al. 2004; Norris 2001): 1) income inequality, 2) investment in research and development (R&D), and 3) national expenditures on secondary education. I argue that these factors are related specifically to digital learning inequality among the 15-year-olds who are the subject of my research, for the following reasons:

First of all, countries with more unequal income distribution tend to distribute educational resources more unevenly (Chiu and Khoo 2005; Chudgar and Luschei 2009), which aggravates the digital learning gap. Second, R&D spending signals a commitment by a country to become more competitive and innovative. This commitment fosters a shared vision for the future that can serve as an inspiration for educators and students alike, even before any particular investments bear fruit (Drori 2006, 2010). Third, expenditures on secondary education can have a direct and immediate influence on the digital access, skills, and aspirations of all students, especially if the funds are used for Internet-enabling classrooms and training educators (Dutton et al. 2004; Erichsen and Salajan 2014). Note that the main research question addressed in this dissertation is not whether these investments in R&D and schools have a *causal* impact on education, but rather whether they are potentially effective tools that nations can use to reduce the new form of inequality referred to as digital learning inequality.

In Chapter 4, I further address whether the effects of R&D investment and educational expenditures on digital learning inequality vary significantly between rich countries and poor countries. The variation of these effects may reflect the different social, economic, and institutional contexts in each country. As Corrocher and Ordanini (2002) notes, "research works have often noted the existence of relevant differences between [developed and developing countries], but have not been able to explain them in terms of different 'speeds' of digitalization (10)". National investments in research, technology, and education may mitigate digital inequality in some nations, but intensify it in others. In poor countries, for instance, it is possible that widespread poverty and lack of social mobility limit the role of the governments in redistributing resources to promote digital learning opportunities.

As noted above, Chapter 5 focuses on cross-national variation in digital learning inequality at the school level. It also examines the role of school investment in digital technology. I ask whether the use of digital technology in schools reduces the relative advantage of attending high-SES schools. Both quantitative and qualitative research suggests that school computer use does not significantly improve disadvantaged students' computer skills or digital literacy (Becker 2000; Margolis et al. 2003; Robinson 2014; Warschauer, Knobel, and Stone 2004; Zhong 2011). Until recently, however, these two rich bodies of research were limited: On the one hand, quantitative research considers only digital investment at the school-level (e.g., computer-student ration, percentage of computers connected to the Internet), which does not reflect how individual students use digital technology in the classroom. On the other hand, less-developed countries have received much less attention from previous qualitative researchers who have based their research on affluent nations. To partially fill these gaps in the literature, I directly test the effect of digital use at school on digital learning outcomes at the student level,

and examine how this relationship differs between schools and varies across countries.

In Chapter 6, I turn to focus on Shanghai and Taiwan. I examine how the patterns of digital learning inequality *within* and *between* schools differ between these two societies and certain other countries. The excellent academic achievements in East Asian societies, especially in Shanghai, have garnered considerable attention (Driskell 2014; OECD 2011a:83–115; Ripley 2014; Sellar and Lingard 2013). To date, however, there is a dearth of research about the effects of family background and school factors on digital learning for East Asian students. The analysis of this chapter contains three parts: First, I compare the difference in the magnitude of digital learning inequality between Shanghai and Taiwan. Second, I examine how the patterns of digital learning inequality in Shanghai and Taiwan differ from seven other economically advanced or newly industrialized countries (NICs), including Hong Kong and Singapore, the other two Chinese societies. Third, I run an analysis that includes 67 countries, for the purpose of understanding how the inequalities of digital learning in Shanghai and Taiwan are different from the rest of the world.

In Chapter 7, the final chapter, I summarize the main findings based on the three empirical chapters, explain the contributions of the research, and discuss the implications and limitations that should be considered for future research.

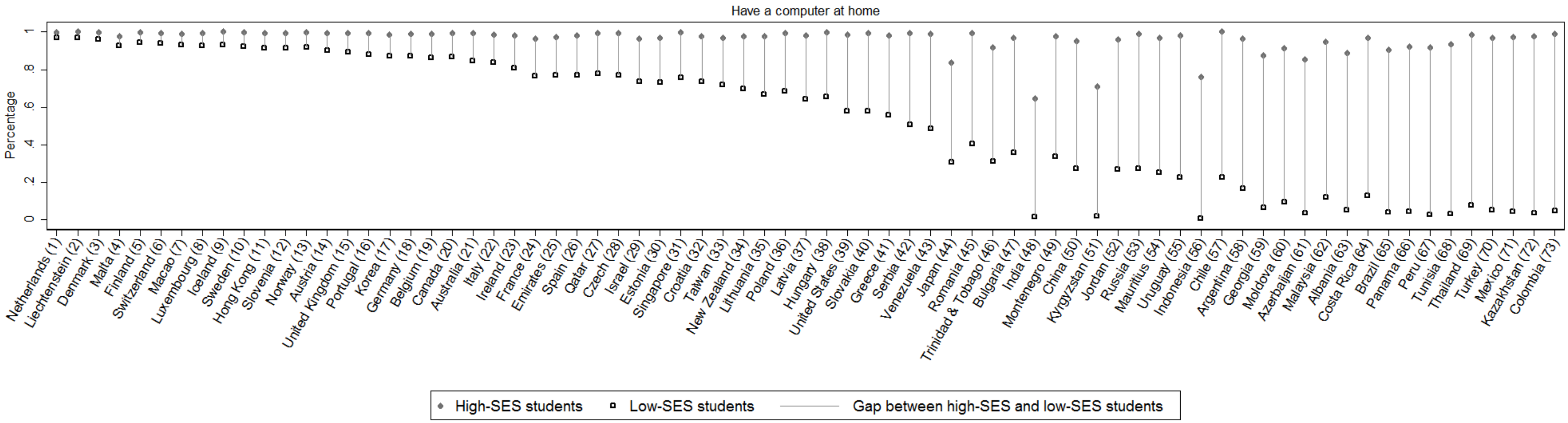

Figure 1.1: Percentage of Students Who Reported Having a Computer at Home by Student SES

Note: The line attached to each country represents the size of the gap between the average of high-SES students (i.e., the top decile of family SES distribution) and the average of low-SES students (i.e., the bottom decile of family SES distribution). Countries are ranked in descending order of the size of the gap between high-SES and low-SES students.

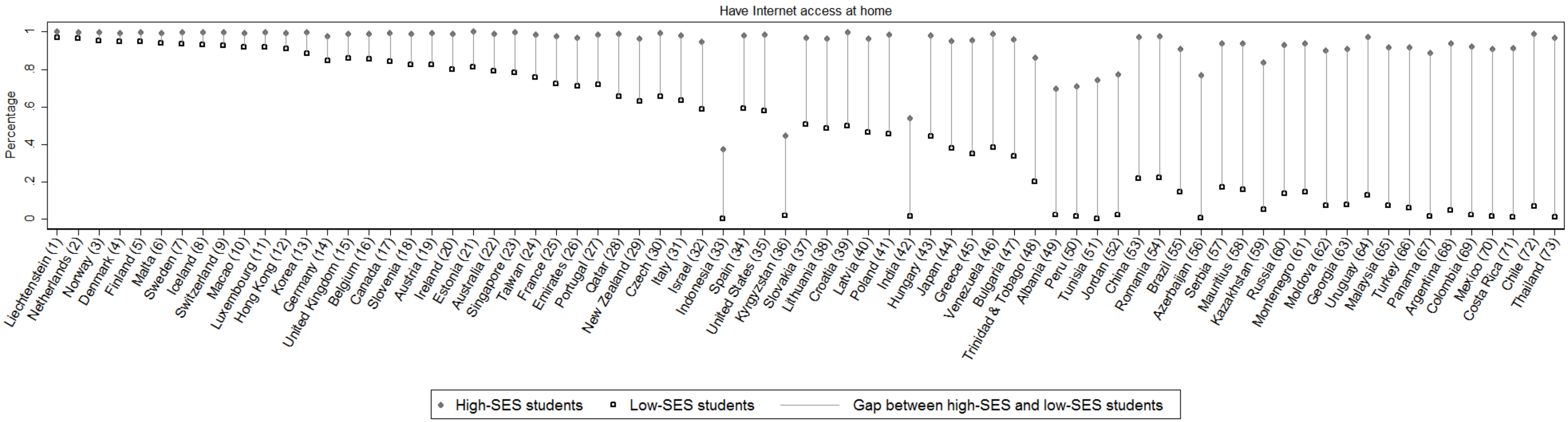

Figure 1.2: Percentage of Students Who Reported Having Internet Access at Home by Student SES

Note: The line attached to each country represents the size of the gap between the average of high-SES students (i.e., the top decile of family SES distribution) and the average of low-SES students (i.e., the bottom decile of family SES distribution). Countries are ranked in descending order of the size of the gap between high-SES and low-SES students.

Chapter 2:

Literature Review: Explanations of Digital Learning Inequality

In this chapter, I begin by reviewing previous literature that focuses on individual- and school-level accounts of digital learning inequality. Moving up to the country-level, I explain how several national-level contextual factors (i.e., economic development, political freedom, income inequality, R&D, and secondary education expenditures) are associated with digital learning inequality. Lastly, I discuss the *differential effects* by national income level. I suggest that R&D investment, secondary educational expenditures, and school investment in digital technology influence digital learning inequality differently between poor and rich countries.

2.1 Background

2.1.1 Digital Learning Inequality at the Individual-Level

Socioeconomic status (SES) has been demonstrated to predict a host of inequalities in society, including educational attainment, occupation and income, and personal health (Grusky 2001). So it should be no surprise that SES is also a predictor of access to digital technologies. Recent studies have revealed several individual-level determinants of digital access related to various aspects of SES, including income (Martin and Robinson 2007), educational status (Hargittai and Hinnant 2008), family structure, race, and immigration status (see DiMaggio et al. 2004 for a review). In sum, these individual-level accounts establish a clear connection between SES—understood as a combination of income and education—and digital access.

As mentioned previously in Chapter 1, the extent of the first digital divide in industrialized countries has been declining in the past decade, due in large part to intentional

efforts by powerful actors such as governments and large corporations. However, the second digital divide—the divide in skills and use—remains a problem. For example, studies from the United States (Hargittai and Hinnant 2008) and Switzerland (Bonfadelli 2002) suggest that highly educated adults are more likely to do capital enhancing or information oriented activities online, such as visiting websites about national news, health, and financial information, than their less educated counterparts. In Korea, higher class adults are more likely than working class adults to use the Internet for political knowledge (Kim 2008). Each of these studies demonstrates a disparity in digital skills along SES lines, even after digital access is achieved. This suggests that enhancing access alone does not guarantee equal outcomes; that is, merely having access to a computer and the Internet without having the proper skills may do little to reduce already existing inequalities and may instead serve to reproduce or even increase them (DiMaggio et al. 2004; Hargittai and Hinnant 2008).

While much of the previous literature has focused on adults, the digital divide among school-aged children and adolescents is equally, if not more important. The digital skills learned in school and at home influence students' academic outcomes and non-academic behaviors (e.g., Attewell, Suazo-Garcia, and Battle 2003), and the digital inequalities generated at this time are likely to be carried into the future. One early source of this inequality is family socioeconomic background. Leu et al. (2014) find that students growing up in economically advantaged neighborhoods are one year ahead of students in less privileged neighborhoods when it comes to online research and comprehension skills. Recent studies in the U.S. (Attewell 2001; Attewell and Battle 1999), Britain (Livingstone and Helsper 2008), and Australia (Smith et al. 2013) suggest that students with highly educated parents are more likely to use computers or the Internet for learning. This is due in part to their parents' active involvement, often sitting with

and supervising their children's computer use. Likewise, findings from the Netherlands (Peter and Valkenburg 2006) and Hong Kong (Leung and Lee 2012) find that the first digital divide in Internet access has been greatly reduced, but lower SES students still tend to use the Internet mainly for gaming or social networking. This, again, suggests a problem of the second digital divide among youth.

2.1.2 Digital Learning Inequality at the School-Level

Disparities in the rates of digital access between schools, in terms of computer use and Internet access, has largely narrowed, particularly among higher income countries (OECD 2011b; UNESCO 2015; Vigdor et al. 2014; Wells and Lewis 2006). However, previous studies find a persistent digital learning gap along the line of school's socioeconomic composition (Leu et al. 2014; Natriello 2001; Warschauer et al. 2004). Comparing California's public high schools, for example, Warschauer (2004) finds that while schools' student-computer ratios are similar, teachers and administrators in low-SES schools have less experiences and fewer professional credentials compared to those in high-SES schools. Scholars also note that low-income and disadvantaged students tend to attend schools with low educational quality and severe budget deficits (Natriello 2001), where there is no provision of courses with clear guidance of digital learning or computer lab for practice (Robinson 2014).

In a similar vein, a large body of research on comparative education suggests that schools with a concentration of socioeconomically disadvantaged students have less available resources for learning and lower quality of teaching (Montt 2011; Park and Kyei 2011; Schmidt et al. 2015). With a comparison of 33 countries, for instance, Schmidt et al. (2015) find that the proportion of the academic achievement gap explained by school SES is appreciable worldwide, especially among countries with a greater proportion of poor students segregating in low-SES

schools. They attribute this achievement gap to differences in opportunity to learn (OTL), measured by the degree of instructional content coverage or content exposure. Chiu and Khoo's (2005) study of 41 countries shows a strong relationship between school mean parent SES and students' academic achievement, which is mediated by the number of certified teacher and education/teacher material shortage. Based on this *school resource* explanation, low-SES schools will fail to promote digital learning opportunities due to their lack of basic educational resources, such as sustained financial budgets, teacher competencies, and course instructions.

Despite the importance of school resources and teacher quality, it is equally important to examine the effects of schools' cultural processes and institutional settings on educational inequalities (Agirdag, Van Houtte, and Van Avermaet 2012; Binder, Davis, and Bloom 2016; Bowles and Gintis 2002; Coleman 1987; Entwisle, Alexander, and Olson 2005; Jack 2016). Building on Bowles and Gintis' (2002) correspondence principle, schools immerse students in different types of cultural models: working-class students are socialized to accept a set of rules and beliefs that conform to working-class jobs (e.g., punctuality, obedience, and authority), whereas middle-class peers are instructed by teachers to learn skills that prepare them to attain upper-class job positions (e.g., critical judgments, creative thinking, and leadership). Related research on students' sense of futility and schools' futility culture explains that students in low-SES schools feel the lack of control over their academic success and believe the school is working against them (Agirdag et al. 2012). Highlighting the role of secondary schools in equipping students with the cultural competencies prior succeeding in college, Jack (2016:2) finds that "lower-income undergraduates who attended boarding, day, and preparatory high schools enter college with a propensity for an ease in engaging authority figures akin to middle-class students. In contrast, the doubly disadvantaged—lower-income undergraduates who

remained tied to their home communities and attended local, often distressed high schools—tend to withdraw from engaging authority figures and feel uneasy when forced to interact with professors." This indicates the teacher-student relationship to be more positive and constructive in resource-rich, elite schools, regardless of students' family backgrounds, compared to that of financially distressed and resource-poor schools.

The cultural and institutional settings of schools may also account for the impact of school average SES on individual students' experiences relevant to their digital use at school. For example, Becker et al (2000) find that while computers are actually being used more frequently in low-SES schools than in high-SES schools, teachers in the former schools tend to use computers for remedial purposes, whereas teachers in the latter schools use computers for more constructivist and innovative ways (e.g., analyze information and make presentations). Comparing across two Hawaiian schools, Warschauer (2000:17) notes that the school located in an extremely poor neighborhood "socializes students into the workforce", whereas the elite preparatory school "socializes students into academia." Similarly, Margolis et al's (2003) research on three Los Angeles' schools conclude that students in a low-resourced school are relegated to low-level vocational computer courses, whereas most students in a predominately white and wealthy school attend high-level college preparatory, computer science classes.

2.2 Digital Learning Inequality in National Context

2.2.1 Economic Development

Between 1990 and 2000, the rates of computer ownership and Internet use have expanded globally, but the expansion has been more dramatic in high-income countries than in middle- or low-income countries (Drori 2006; ITU 2011). Scholars suggest that economic development is one of the strongest predictors in explaining cross-national differences in Internet connectivity

(Guillén and Suárez 2005; Norris 2001). As economic development improves people's living conditions, the poor spend relatively less of their resources on necessities (e.g., food, housing) and have more money to spare for digital devices. Moreover, economic development leads to a growing demand and supply of digitally networked technology (Robison and Crenshaw 2010), promotes both public and private investments on Internet infrastructure (e.g., high-speed Internet landlines and community e-service) (Guillén and Suárez 2005), reduces the absolute price charged for online access (Hilbert 2010), and, therefore, increases people's motivations for new technology use (Guillén and Suárez 2005; Norris 2001). Norris (2001:233–34) states that economically advanced countries have wide access to various information and communication technologies through public resources, like wired schools, digitalized libraries, and networked community centers; on the contrary, many developing societies face "multiple barriers where access to household telephones and television remains uncommon, as well as reliable supply of electricity, let alone computers."

In sum, Baker et al (2002:297–98) note that there might be a "cumulative effect of national income (presumably acting through both enhanced national levels of family SES and school resources) [that] will lead to greater national achievement production." While there are no direct comparative studies of the digital learning inequality among youth, I would expect a similar relationship between economic development and the level of digital learning inequality: the gap in digital skills between students from low SES homes versus students from high SES homes will be less in affluent countries than in poor countries. That is, increases in economic development should lead to reductions in the level of the digital learning inequality across levels of SES.

2.2.2 Political Freedom

Scholars have also suggested that the degree of political freedom or democraticness of government in a society may determine the level of the digital divide (Norris 2001). When basic civil liberties such as freedom of speech and freedom of the press are protected, individuals are more likely to access the Internet and engage in various forms of online education, discussion, and political action. In contrast, non-democratic governments may be less likely to try to bridge the digital divide by making Internet access widely available in public spaces such as schools or libraries. The intuitiveness of this argument notwithstanding, some scholars suggest that economic factors tend to outweigh political freedom and democratization in determining the digital divide. For example, Corrales and Westhoff (2006) explain that not all authoritarian governments are against Internet diffusion. In particular, authoritarian states that are market-oriented have less restrictions on Internet use. In line with this argument, Robison and Crenshaw (2010) demonstrate that democratic governance and political stability only affect Internet development when a country's economy is depressed or stagnant.

Again, while these studies on political freedom have focused just on the digital divide in online access, I expect political freedom to reduce the digital learning inequality. Moreover, I expect that the impact is likely reduced after taking economic development into account.

2.2.3 Income Inequality

Recent scholarship has documented a negative relationship between income inequality and academic achievement (Chiu and Khoo 2005; Chudgar and Luschei 2009). Countries with more unequal income distribution typically have lower social mobility, greater status competition, and higher concentration of poverty (Wilkinson and Pickett 2009). This suggests that income inequality favors students from upper class and more educated families, because they tend to

attend schools with more resources and better financial support (Chiu and Khoo 2005).

Income inequality may also affect the distribution of digital learning resources in schools and society. According to diffusion theory (Rogers 1995), privileged social groups are more likely to have a head start in accessing the newest digital appliances, while the adoption of new technological inventions takes a longer time for less-privileged people (DiMaggio et al. 2004; Martin and Robinson 2007). This indicates that the rate of technology diffusion among poor and less-privileged people will be slower in more unequal countries. Between 1997 and 2003, Martin and Robinson (2007) find that the rate of Internet access in the United States increased most rapidly among high-income population; conversely, the rate increased most slowly among low-income population. They further note that the link between family income and Internet adoption is stronger in the U.S. than in most European countries, where the level of income inequality is relatively lower. In their comparative study of five country, Ono and Zavodny (2007) show that inequalities of digital use reflect pre-existing social and economic inequalities. Like income and education, for instance, gender becomes a strong determinant of online usage in countries with greater degrees of gender inequality. This, again, implies that economic inequality may be associated with the inequality in digital learning opportunities.

In this dissertation, I expect that income inequality increases digital learning inequality. That is, the level of the digital divide is higher among more unequal countries than their more equal counterparts. Taking together, these previous findings tell us that national contextual factors such as economic development, political structure, and income inequality should be considered when studying the digital divide among school-aged children.

2.3 Beyond Economic and Political Explanations

In the final decades of the 20th century there were just a few national-level efforts to promote the

use of technology in the education of students (Erichsen and Salajan 2014; U.S. Department of Education 1996). Since then, the quantity and urgency of these national efforts has increased significantly (Spring 2008), often inspiring competition among countries trying not to lag behind in the digital revolution. Such competition has become prevalent among the most developed nations, especially between the U.S. and Western European countries (Erichsen and Salajan 2014). Although studies in less-developed countries indicate a growing commitment to increasing digital literacy as well, their abilities to support digital learning policies are more limited due to the highly unequal global distribution of resources (Drori 2006, 2010; UNESCO 2015). To further examine how this global inequality affects a country's ability to bridge the digital divide among students, I consider whether national investments in R&D and educational expenditures on secondary education affect the digital divide. These two factors differ from economic development and democraticness of society in at least one fundamental way: unlike the levels of economic development or democracy, which are difficult to change in the short term, governments can immediately and directly increase or decrease their levels of investment in R&D and secondary education.

I readily acknowledge that the content of R&D and educational investments can vary greatly among countries and that, in some cases, they may not at all be connected to digital learning or the disparities in computer use and skills. For example, it is possible that the R&D investment of a nation may not focus on digital technologies, but rather on the development of new medications or military weaponry. In other cases, when R&D is directly focused on digital technology, it may not directly affect students. On the other hand, while educational expenditures have a clear and direct relationship to students, countries may distribute their educational resources in ways that are unrelated to digital technology use. It is also possible to envision the

distribution of educational investments within a country being biased by social status, with the newer technologies going only to the schools in the most affluent areas. Bearing these possibilities in mind, this dissertation examines whether or not these investments, when used appropriately, may serve as tools to reduce the inequalities of digital learning. Below, I elaborate the paths by which the two investments may potentially affect the gaps in digital skills and usage among students.

2.3.1 R&D

Many scholars have referred to the rapidly changing world economy as the new "knowledge economy," characterized by massive information flows worldwide, extensive adoption of new information technology, and scientific and technology advancement (Dale 2005; Powell and Snellman 2004; Spring 2008). Spending on R&D, by both the public and the private sectors, signals a pledge by a country to become more competitive and innovative and to play an active role in the new knowledge economy. The benefits of R&D, however, are not limited to just the economy. R&D produces spillover effects that can affect many other areas of social life, including agriculture, medicine, entertainment, and most relevant to this dissertation, education (Drori 2006). R&D investment can also reduce the dependency of less-developed countries on affluent countries for technology transfers (Choi 1999), a notable point considering the growing consensus among scholars that a country's innovation capacity positively affects its adoption of digital technology (Drori 2010).

In particular, R&D spending from both public and private sources is often piloted in educational settings (Snow 2002; Spring 2008). Heyneman and Loxley (Heyneman and Loxley 1983:1183–84) note that "the areas of the world with comparatively large amounts of research and development capital tend also to be the areas where educational paradigms are invented."

For example, the Australian Government created a platform that enables schools to share and distribute educational resources through online portals (Education Services Australia 2012). In the U.S., the invention of cyber schools is regarded as a new opportunity to students who have failed in the conventional school system (Hill 2010). A great deal of computer and technology equipment currently in schools has been donated by major corporations, such as Microsoft, Intel, Hewlett-Packard and AT&T (Norris 2001).

Regarding poor countries, Information and Communication Technologies for Development (ICT4D) is a global initiative that works closely with several agencies, such as governments, universities, public schools, and private organizations to reduce digital inequality (UNESCO 2016). Experiences from some developing countries—like Korea in its 1980s—show a successful developmental strategy that combines schooling reforms with new knowledge transferred from transnational and multinational corporations (Hanson 2006). Recent scholarship further highlights the problem of developing countries lacking national support on R&D and relying on foreign sources of funding and expertise for national development, which end up overlooking the needs of local people, schools, and communities (Dutton et al. 2004). Linking the global digital divide with the "global innovation divide," Drori (2006, 2010) states that most affluent countries have higher capacity of technology innovation and possess more intellectual property related to the new technology. These higher innovative capabilities are likely to affect students' learning in a way that more educational apps and online learning resources are extensively diffused and used. In contrast, students of poor and low-innovative countries are restricted from using these digital resources as long as technologically advanced countries try to protect technology innovations through the intellectual property.

Taking into consideration these findings of past research—that R&D has spillover effects

throughout society, that it reduces the dependence of less-developed countries on technology transfers, and that it is often utilized directly in educational settings—I expect that the national level of investment in R&D will reduce digital learning inequality. In other words, to be able to successfully compete in the knowledge economy, a country must have a digitally literate population. Thus, as the knowledge economy takes hold, the use of digital devices and the corresponding digital skills will spread throughout the population, potentially reducing the digital divide.

2.3.2 Educational Expenditures

Globally, the level of spending per pupil on primary and secondary education has surged over the past two decades (Baker et al. 2002; Cohen et al. 2006), marking a substantial increase in national investments in the production of human capital. This investment affects the educational outcomes of students, particularly those from less affluent households (Chiu 2010). As a result, many scholars have explored how public expenditures on education are associated with the educational attainment gap between low- and high-income children (Mayer 2001; Vegas and Coffin 2015).

In addition to affecting student achievement in the core academic areas, this form of public investment in educational institutions may reduce the inequalities of digital learning by leveling the playing field for students from socio-economically diverse backgrounds. Qualitative research suggests that substantial inequality persists in digital use at school. This inequality is due primarily to the insufficient digital access and guidance in the use of digital technology for less-affluent students (Goode 2010; Natriello 2001; Robinson 2014). For instance, Natriello (2001) points out that racial minority and socioeconomically underprivileged students tend to attend schools with extremely low educational quality and severe budget deficits. Robinson

(2014) finds that students with the greatest need for digital use at high school are less likely to take advantage of courses that offer guidance of digital learning and computer lab for practice.

Researchers propose that schools should play a greater part in mitigating the digital divide by providing computer access and the kinds of guidance required for students to develop the skills that make digital technology a valuable tool in learning (Gamoran 2001; Robinson 2014). In countries or regions where students do not have a computers or internet connections at home, it is all the more important for schools to provide those things to overcome the divide. Based on the fact that there is considerable variation in public spending on education even among countries with similar economic standing, I propose that higher levels of national expenditures on secondary education are associated with lower levels of the digital learning inequality among students.

2.4 Differential Effects between Poor and Rich Countries

A worldwide initiative to improve the use of digital technology in education has emerged in the developing world (Beuermann et al. 2013; Bhanji 2012; James 2010; UNESCO 2000, 2015; UNESCO-UIS 2015). A widely held belief is that there is a need for governments to find ways to reduce digital learning inequalities. However, because previous literature on the digital divide is primarily conducted in developed countries, particularly the U.S. (Attewell 2003; DiMaggio et al. 2004; Hargittai and Hinnant 2008; Leu et al. 2014) and other Western societies (Bonfadelli 2002; Livingstone and Helsper 2008; Looker and Thiessen 2003; Peter and Valkenburg 2006), what policies, projects, or practices are directly related to the task of bridging the digital divide in poor countries have not been tested. A key issue in this discussion is to account for the vast diversity of students' life experiences and educational trajectories in different regions of the world, especially noting the institutional variation between the developed and the less-developed

countries (Buchmann and Hannum 2001; Juárez and Gayet 2014). In what follows, I first explain how social inequality and widespread poverty in less-developed countries may limit a country's ability to bridge the digital learning divide among educating youths. I then address whether the use of digital technology at school reduces the digital learning inequality between schools, and how this effect may differ between poor and rich countries.

2.4.1 Life Paths and Educational Opportunities in the Developing World

Social inequality and poverty, in addition to the recent global economic crisis, determine the life paths and educational opportunities of young people in less-developed countries (Fussell, Park, and Costa Ribeiro 2010; Juárez and Gayet 2014; Pastore 2009). Despite the significant increase of educational expenditures and the expansion of school enrollment in this region of the world, school systems fail to offer equal educational opportunities to students from unfavorable family backgrounds (Juárez and Gayet 2014; Pastore 2009).

In Moldova, for example, poverty and lack of job opportunity affect how children learn at home and in school. Many children are left to the care of relatives and grandparents because their parents have gone abroad to work. There is also a lack of qualified teachers in schools, as many teachers emigrate for overseas work (Worden 2014). In addition, education marketization has become another striking issue among many poor countries, which result from the governments not being able to continue to support publicly funded education. The reliance of private providers in education and the increase in the number of private schools have limited the educational opportunities of poor and underprivileged students (Chankseliani 2014).

Considering these possibilities, I argue that the role of the governments in reducing digital learning inequality is limited in the developing world. This is possibly due to the fact that the benefits of national investment in technology, science, and education is limited to the most

affluent and privileged students. In Chapter 4, I further examine how the effects of R&D spending and educational expenditures on the inequality of digital learning may vary depending upon the wealth of a country. I propose that the effects for R&D spending and educational expenditures is smaller in reducing digital learning inequality for students in less-developed countries.

2.4.2 School Investment in Digital Technology

How does school investment in digital technology affect existing inequalities in the availability of digital learning opportunities between schools? In other words, does the use of digital technology at school reduce the relative advantage of attending high-SES schools?

Many scholars have questioned the importance of school investment in digital technology, and suggested that school computer use does not necessarily improve disadvantaged students' digital learning (Natriello 2001; Vigdor et al. 2014). Quantitative researchers find very limited evidence to support the positive relationship between schools' investment on digital technology and students' digital skills (Becker 2000; Zhong 2011). Similarly, qualitative scholars suggest that less-privileged and disadvantaged students receive less institutional support to enhance their digital literacy (Warschauer et al. 2004) and are less likely to take advanced computer courses (Margolis et al. 2003; Robinson 2014). I argue that most quantitative research only considers digital investment at the school-level (e.g., computer-student ratio), but not the quantity and quality of digital use at school among individual students. Moreover, the qualitative scholars mostly base their findings on more-developed countries and we do not know if these results can be applied to the developing world. To partially fill these gaps in the previous literature, I directly examine the effect of digital use at school at the individual-level in both economically more- and less-developed countries.

I contend that the use of digital technology at school is positively associated with digital learning, but the magnitude of this relationship differs across schools and varies cross-nationally. In poor countries, on one hand, the positive relationship may be stronger in lower-SES schools than higher-SES schools. This, which I refer to as *the marginal utility hypothesis*, suggests that increased investment in digital technology at school produces greater benefits for schools with a majority of socioeconomically disadvantaged students, where basic educational resources are limited or unequally distributed and most students have no computer or high-speed Internet access at home. The marginal utility of further investment in digital technology in socioeconomically advantaged or resource-rich schools may be diminished due to already high levels of investment in educational resources, and by the fact that a majority of students have access to digital learning opportunities at home.

In rich countries, on the other hand, high-speed Internet access and digital learning opportunities are more available in schools, libraries, community centers, and individual households. I propose that the increasing use of digital technology in the classroom does not reduce the relative advantage of attending a higher-SES school. This argument is based on recent scholarship which highlights persistent and "maximally maintained" educational inequalities among affluent countries, despite their high levels of educational expansion and investment in human capital (Hannum and Buchmann 2005; Raftery and Hout 1993). Drawn from Bourdieu (1984), once learning opportunities become widely accessible to children regardless of their backgrounds, children from privileged families will reproduce their relative advantage by acquiring prestigious educational credentials and taking exclusive practices. Thus, privileged students may regard retrieving advanced computer skills and Internet-search related knowledge as a key of status distinction and academic success—an achievement that may differentiate

themselves from other students having digital access without related skills. In contrast, schools with more disadvantaged and low-income students tend to use technology for remedial purposes (Becker 2000; Warschauer et al. 2004).

According to *the complementary perspective*, intangible resources—such as students' attitudes (Coleman 1987), parents' time and attention to support children (Schiller, Khmelkov, and Wang 2002), and teacher-student interaction (Chiu 2010)—replace the importance of tangible school resources in determining students' academic success when countries become more industrialized and economically advanced. Because "many families at all social levels fail to provide an environment that allows their children to benefit from schools as they currently exist (Coleman 1987:36)", high-SES schools tend to have more intangible school resources that facilitate students' learning experiences. In more affluent countries, this suggests that the positive effect of digital use at school on digital learning is stronger for students attending higher-SES or elite-schools than students in lower-SES or resource-poor schools.

In sum, I incorporate both the marginal utility hypothesis and the complementary hypothesis to enhance my understandings of cross-national variation in the inequalities of digital learning between schools (see Chapter 5). Based on the aforementioned explanations, I argue that national economic development moderates the mechanism of educational stratification as well as the pattern of digital learning inequality, which explains why the marginal utility hypothesis is more explainable in less-developed countries and the complementary hypothesis is more appreciable among more-developed countries. By combining the two theoretical hypotheses, we should also see that the more comprehensive use of digital technology in schools may further reduce the digital divide between schools in poor countries, whereas this relationship may not exist among rich countries.

Chapter 3:

Data, Measures, and Methods

3.1 Data

The primary source of data is the 2009 wave of the Programme for International Student Assessment (PISA), collected by the Organization of Economic Cooperation and Development (OECD). PISA is uniquely suited to examine digital learning inequality from a cross-national perspective because it focuses on students' reading performance in both printed texts and digital materials, including a variety of questions related to students' behaviors and attitudes regarding digital use. Equally important, it includes data for countries from a wide range of economic backgrounds. The original sample contains 73 countries (see Figure 3.1), but due to missing data on country-level variables I restrict the analyses to 55, 42, and 67 countries in Chapters 4, 5, and 6, respectively. To preserve cases, I utilize multiple imputations (*m*=10) for missing values in the individual-level control variables (Royston, Carlin, and White 2009). The original sample size of students across 55 countries is 402,671. Appendix 3.1 presents map indicating the countries which were participants of the PISA 2009 survey.

[Figure 3.1 about Here]

3.2 Measures

In this dissertation, I focus on the impact of country-level variables on the inequalities of digital learning at the student-level. I include three dependent variables in order to measure the degree of digital learning inequality: The first, *use of educational software at home*, is a dichotomous variable that asks students if there is "educational software in your home." Students with educational software at home are coded as 1 and those without are coded as 0. While this

variable only represents one type of digital use, it indicates the likelihood of students to use a computer for productive and educational purposes. The second dependent variable, *digital use for schoolwork at home*, is a composite score containing five activities at home: browsing the Internet for schoolwork, using e-mail to communicate with other students about schoolwork, using e-mail to communicate with teachers and submit schoolwork, using material from the school website, and checking the school website for announcement. Each component represents a particular aspect of online usage at home that directly relates to school-related work. The variable is standardized with a mean of 0 and a standard deviation of 1. The third dependent variable, *Internet literacy*, is a composite scale measuring how often students engage in the following five online reading activities: reading online news, using an online dictionary or encyclopedia (e.g., Wikipedia), searching online information to learn about a particular topic, taking part in online group discussions or forums, and searching for practical information online (e.g., schedules, events, tips, recipes).[1] Each component represents a particular aspect of online reading habits and the associated skills. A combination of these items indicates how familiar students are with reading text on the screen, sharing information and exchanging ideas, and interacting with others in a digital context. The variable is standardized with a mean of 0 and a standard deviation of 1.

I use *family SES* as the key independent variable, which is based on the PISA-created Index of Economic, Social, and Cultural Status (OECD 2012)—the most commonly used measure of SES in studies using PISA data. The variable is a combination of three components: parental occupation status expressed as the index of the international socio-economic index of occupational status (ISEI) (Ganzeboom, De Graaf, and Treiman 1992), parental education in

[1] In the questionnaire, there were seven online reading activities. I exclude two of these activities—reading emails and chatting online—as they are not directly related to searching for information or acquiring knowledge.

years, and an index of household possessions, such as a room for the child, owning classical literature, a desk for the child to study at home, and the number of books at home. To ease interpretation of the results, the variable is standardized to have a mean of 0 and a standard deviation of 1.[2] In addition, I include six individual-level control variables. *Gender* controls for the potential digital gap between male and female students (male=1). Because PISA samples 15-year-old students regardless of the grade they attend, I control for *school grade*. Students attending school at the same grade as most other students of the same age within their country are coded as 0. A negative integer (-1, -2, etc.) or a positive integer (1, 2, etc.) indicates the number of years students are either below or above their expected grade level. To control for the impact of immigration status, I include two dummy variables—*first generation immigrant* and *second generation immigrant*—with *non-immigrant student* as the reference category. To control for differences in language used by immigrant students I include a dummy variable—*foreign language use at home*—with *use the same language at home as in school* as the reference category. I include this control because students that are not native speakers of the language used at school can often be academically disadvantaged compared to native-speaking students. To control for the effect of family structure, I include two dummy variables—*single-parent family* and *other family*—with *two-parent family* as the reference category.

At the school-level, *school SES mean* is an average of the student-reported family SES for each school, used to address the impact of the socioeconomic composition of the schools. I use this variable to examine the degree of digital learning inequality at the school-level (i.e., the effect of *school SES mean* on the two dependent variables). I also include further school-level control variables, which are derived from the PISA 2009 questionnaires for each of the schools,

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[2] Some studies use the number of books at home as a proxy for family SES or social class (Carnoy and Rothstein 2013). I consider this alternative in supplementary analyses and find the results to be substantively the same.

which are completed by school principals. To control for the difference between rural schools and schools in urban areas, I include two dummy variables—*rural* and *town*—with *city* as the reference category. To control for the time and attention that teachers give to individual students, I use the variable *class size*, which is the average class size of the language of instruction calculated from students' self-reports (OECD 2010a:82). In the questionnaire, students were asked, "on average, about how many students attend your <test language> class?" To account for the effect of teacher attributes, I include *teacher shortage*, a PISA-created index indicating the lack of teachers in four fields: science teachers, mathematics teachers, qualified language teachers, and qualified teachers of other subjects. Original response categories, from lower to higher values, are: "not at all", "very little, "to some extent", "and "a lot". To control for a school's overall educational resource quality, I use another PISA-created index, *school resource quality*, which measures the shortage or inadequacy of seven items: science laboratory equipment, instructional material (e.g., textbooks), computers for instruction, Internet connectivity, computer software for instruction, library materials, and audio-visual resources.

To examine cross-national differences in digital learning inequality, I compile a set of country-level factors from a variety of publicly available sources. To measure a country's economic standing, I use *Gross Domestic Product (GDP) per capita*, in thousands of 2009 purchasing power parity (PPP) dollars, obtained from the World Bank's World Development Indicators (2015c). I use the *composite polity score* to measure the level of political freedom. This is a combined democracy-autocracy index developed by Marshall, Gurr, and Jaggers (2010). The scale ranges from -10 (strongly autocratic) to 10 (strongly democratic). To measure a country's investment in R&D and secondary education, I include R&D as a percentage of GDP from the World Bank's World Development Indicators (2015c) and educational expenditures as

a percentage of GDP from the World Bank's Education Statistics (2015a). All of the country-level data are from 2009—the year that the individual-level PISA data were collected.[3] Natural log values are used for all country-level variables to account for the skewness of the distributions (Ruiter and van Tubergen 2009) and to address potential curvilinear relationships (Heisig 2011).

3.3 Methods

To account the hierarchical nature of my data (i.e., student-, school-, and country-level data), I make use of multilevel methods. Without considering the multilevel structure and the dependence across observations from the same school or the same country, the standard errors will be underestimated which would lead to wrong conclusions (Rabe-Hesketh and Skrondal 2008; Raudenbush and Bryk 2002).

Because different empirical chapters address quite different research questions, I will discuss the statistical methods and equations later in each empirical chapter.

[3] For countries that have missing data on country-level variables in 2009, I utilize data from the closest adjacent year in which data is available.

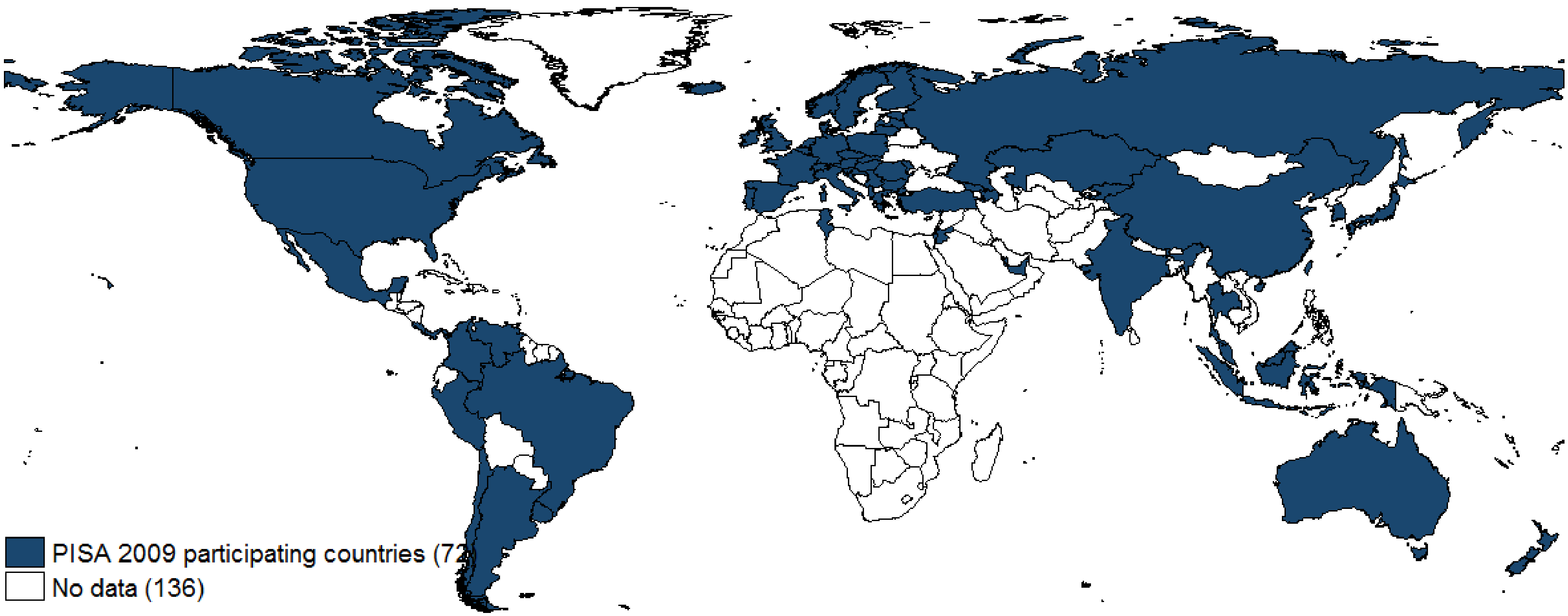

Figure 3.1: A Map of PISA 2009 Participating Countries and Economies

Chapter 4:

Inequality of Digital Learning Between Students

In Chapter 2, I reviewed the existing literature and explanations on digital learning inequality. After laying the groundwork for the study, I also reviewed the methodology of the present analysis in Chapter 3. In this chapter—the first empirical chapter—I examine cross-national variation in the inequalities of digital learning between students from various socioeconomic backgrounds. Related research agendas arise as to what explains cross-national variation in digital learning inequality; does national investment in research, innovation, and education help reduce digital learning inequality; and how does national wealth affect a country's ability to bridge the digital learning divide?

4.1 Problem Statement

Bridging the digital divide between more and less privileged students has become an important agenda for policy makers, scholars, and parents. In response to this task, there have already been numerous national and international efforts to combat the digital divide (for instance, see Beuermann et al. 2013; Chen 2007; Culp et al. 2003; Erichsen and Salajan 2014; Spring 2008; UNESCO 2000, 2015; White House 2013). Despite these efforts, however, the inequalities of digital learning persist among students, which has been found to be a problem for all countries, including both rich and poor countries (DiMaggio et al. 2004; Drori 2010; ITU 2011; Livingstone and Helsper 2008; Notten et al. 2009). Therefore, there is a need to theorize how the digital learning inequalities among students differ systematically across countries, which would help the governments to find out potential solutions to the digital divide.

In this chapter, I examine the level of digital learning inequality among 15-year-olds

across 55 countries. I ask the following research questions: At the national level, what are the key determinants of the digital learning divide by SES, and what kinds of national investments are important in reducing digital learning inequality? To address these questions, I focus on several country-level indicators: I beginning with an examination of how economic development and political freedom affect the level of digital inequality within a country. This is based on the existing digital divide literature on adults which has focused on general indicators such as economic development and democracy (Corrales and Westhoff 2006; Guillén and Suárez 2005; Hargittai 1999; Norris 2001; Robison and Crenshaw 2010). Moving beyond economic and political explanations, I further explore two national investments that have recently received much attention in research on comparative education (Dale 2005; Erichsen and Salajan 2014; Spring 2008) and the global digital divide (Drori 2006, 2010; Dutton et al. 2004; Norris 2001), which include investment in research and development (R&D) and national expenditures on secondary education. I argue that these national investments play a significant role in students' digital learning opportunities, because they represent the commitment of a nation to preparing the next generation for the new digital world.

In the analysis of this chapter, I center on two aspects of digital learning inequalities, which include the gaps in 1) educational software use at home and 2) Internet literacy. I expect that increasing economic development and political freedom reduce the digital learning divide along the socioeconomic line. However, as noted in Chapter 2, the effect of economic development should be greater than that of political freedom. I propose the following research hypothesis:

Hypothesis 4.1: Higher levels of national income and political freedom are associated with lower levels of inequalities of digital learning among students,

and the magnitude of the effect is stronger for national income than political freedom.

Moving beyond the explanations that center on economic development and political freedom, I also examine if R&D investment and expenditures on secondary education affect the inequalities in digital learning. In Chapter 2, I explained that R&D has spillover effects on many areas of social life, such as agriculture, entertainment, and education—the most relevant area to this study (Drori 2006). R&D also signals a country's innovation capacity in developing new information technology which is utilized directly in educational settings (Snow 2002; Spring 2008). Moreover, public expenditures on education may affect digital learning opportunities. Scholars suggest that schools should play an active role in mitigating the digital divide by providing computer access and the kinds of guidance required for students to develop the skills that make digital technology a valuable tool in learning (Gamoran 2001; Robinson 2014). In countries or regions where low-income students have no access to a computer or the Internet at home, in particular, it is all the more important for schools to provide those things to overcome the divide. Based on these, I expect that:

Hypothesis 4.2: Higher levels of national investment in R&D are associated with lower levels of digital learning inequalities among students. Moreover, more national expenditures on secondary education are associated with lower levels of the inequalities of digital learning.

Lastly, I address how the effects of R&D investment and educational expenditures vary across national contexts. Based on a large body of literature, the life experiences of students and educational opportunities in different parts of the world are likely to be different, especially noting the institutional variation between economically more- and less-developed countries

(Buchmann and Hannum 2001; Juárez and Gayet 2014). Therefore, I argue that the roles of R&D investment and educational expenditures in bridging the digital divide among students are different, depending upon the level of national income. Drawing upon previous literature on comparative education, increasing educational expenditures in developed countries may be more beneficial to students from lower-SES or disadvantaged backgrounds (Vegas and Coffin 2015); in less-developed countries, on the contrary, it is likely that increasing educational resources only benefits students from socioeconomically privileged backgrounds. Based on this rationale, I propose that:

Hypothesis 4.3a: The effects for R&D spending and educational expenditures may be smaller in bridging the digital divide for students in less-developed countries.

In the analysis, I also address if the aforementioned hypothesis goes in an opposite direction. The rationale behind of this is based on previous research which states that the marginal utility of further educational investment in rich countries is small due to already high levels of investment (Buchmann and Hannum 2001) and persistent educational inequalities (Hannum and Buchmann 2005; Raftery and Hout 1993). Therefore, I create a competing hypothesis:

Hypothesis 4.3b: The effects for R&D spending and educational expenditures may be greater in bridging the digital divide for students in less-developed countries.

4.2 Data

This chapter compares students across 55 countries, using data from the 2009 wave of the OECD Programme for International Student Assessment (PISA). The original sample contains 73 countries, but due to missing data on country-level variables I restrict the analyses to 55 countries. Using the World Bank (2015b) categorization, this chapter includes 6 lower middle

income countries, 15 upper middle income countries, and 34 high income countries.[4] In the analysis, I adopt this income classification and, to ease explanation, name them as low-income countries, middle-income countries, and high-income countries, respectively. To preserve cases, I utilize multiple imputations (*m*=10) for missing values in the individual-level control variables (Royston et al. 2009). The original sample size of students across 55 countries is 402,671. Dropping missing cases in the dependent variables and the key independent variable—family SES—leads to final sample sizes of 391,261 and 398,681 cases for the two dependent variables discussed below. Appendix 4.1 reports the descriptive statistics for key individual-level variables in each of the 55 countries.[5] Appendix 4.2 reports the values of country-level variables for the 55 countries.

4.3 Measures

4.3.1 Dependent Variables

This chapter focuses on the impact of country-level variables on the inequalities of digital learning at the student-level, operationalized as the inequality in computer use for educational purposes at home and the inequality in Internet literacy. Two measures of computer use for educational purposes at home are available in PISA. The first is a composite IRT score of digital use for schoolwork at home, available for 37 countries. The second is a dichotomous variable of whether students use educational software at home, available for 55 countries. Both variables measure digital use for educational purposes, but the second measure is more narrowly defined.

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[4] In the data year of 2009, lower middle income countries are defined as countries where the Gross National Income (GNI) per capita is below $3,945 in U.S. dollars. The GNI per capita of middle income countries is above $3,946 and below $12,195. The GNI per capita of high income countries is above $12,195.

[5] To account for the possibility of countries with large sample sizes disproportionately affecting the parameter estimates of models, I run supplementary analyses with a variable measuring country sample size and find the results to be unchanged.

Supplementary analyses using the two measures as dependent variables show similar effect patterns, but the estimated effects from the second measure are more conservative than those from the first (see Appendix 4.3). I opt to use the second measure because, despite more conservative estimates, it allows us to examine a substantially larger and more diverse sample of countries (55 vs. 37).

Internet literacy is measured by a composite scale of five online reading activities (α=.79): reading online news, using an online dictionary or encyclopedia, searching online information to learn about a particular topic, taking part in online group discussions or forums, and searching for practical information online (e.g., schedules, events, tips, recipes).[6] Each component represents a particular aspect of online reading habits and the associated skills. A combination of these items indicates how familiar students are with reading text on the screen, sharing information and exchanging ideas, and interacting with others in a digital context. The variable is standardized with a mean of 0 and a standard deviation of 1.

4.3.2 Individual-Level Variables

The key independent variable, *family SES*, is based on the PISA-created Index of Economic, Social, and Cultural Status (OECD 2012), which is the most commonly used measure of SES in studies using PISA data. The variable is a combination of three components: parental occupation status expressed as the index of the international socio-economic index of occupational status (ISEI) (Ganzeboom et al. 1992), parental education in years, and an index of household possessions, such as a room for the child, owning classical literature, a desk for the child to study at home, and the number of books at home. To ease interpretation of the results, the variable is

[6] Seven online reading activities are listed in the questionnaire. I excluded two of these activities—reading emails and chatting online—as they are not directly related to searching for information or acquiring knowledge.

standardized to have a mean of 0 and a standard deviation of 1.[7]

In addition, I include six individual-level control variables. *Gender* controls for the potential digital gap between male and female students (male=1). Because PISA samples 15-year-old students regardless of the grade they attend, I control for *school grade*. Students attending school at the same grade as most other students of the same age within their country are coded as 0. A negative integer (-1, -2, etc.) or a positive integer (1, 2, etc.) indicates the number of years students are either below or above their expected grade level. To control for the impact of immigration status, I include two dummy variables—*first generation immigrant* and *second generation immigrant*—with *non-immigrant student* as the reference category. To control for differences in language used by immigrant students I include a dummy variable—*foreign language use at home*—with *use the same language at home as in school* as the reference category. I include this control because students that are not native speakers of the language used at school can often be academically disadvantaged compared to native-speaking students. To control for the effect of family structure, I include two dummy variables—*single-parent family* and *other family*—with *two-parent family* as the reference category.

4.3.3 Country-Level Variables

To examine cross-national differences in digital learning inequality, I compile a set of country-level factors from a variety of publicly available sources. To measure a country's economic standing, I use *Gross Domestic Product (GDP) per capita,* in thousands of 2009 purchasing power parity (PPP) dollars, obtained from the World Bank's World Development Indicators (2015c). I use the *composite polity score* to measure the level of political freedom. This is a

[7] Some studies use the number of books at home as a proxy for family SES or social class (Carnoy and Rothstein 2013). I consider this alternative in supplementary analyses and find the results to be substantively the same.

combined democracy-autocracy index developed by Marshall, Gurr, and Jaggers (2010). The scale ranges from -10 (strongly autocratic) to 10 (strongly democratic). To measure a country's investment in R&D and secondary education, I include R&D as a percentage of GDP from the World Bank's World Development Indicators (2015c) and educational expenditures as a percentage of GDP from the World Bank's Education Statistics (2015a). All of the country-level data are from 2009—the year that the individual-level PISA data were collected.[8] Natural log values are used for all country-level variables to account for the skewness of the distributions (Ruiter and van Tubergen 2009) and to address potential curvilinear relationships (Heisig 2011).[9] Table 4.1 presents descriptive statistics and coding for all variables used in the analyses.

[Table 4.1 about Here]

To compare the differential effects between affluent and poor countries, this chapter includes 6 lower middle income countries, 15 upper middle income countries, and 34 high income countries, using the World Bank (2015b) categorization.[10] In my analyses, I adopt this income classification and, to ease explanation, name them as low-income countries, middle-income countries, and high-income countries, respectively.

4.4 Analytical Strategy and Statistical Methods

I use multilevel models to analyze the effects of country-level factors on the two dependent variables and to account for the interdependent variations caused by the clustering of students

[8] For countries that have missing data on country-level variables in 2009, I utilize data from the closest adjacent year in which data is available (see Appendix 4.2).
[9] Because the composite polity score ranges from -10, to 10, I take a linear transition by adding 11 before logging to ensure that all values are positive.
[10] In the data year of 2009, lower middle income countries are defined as countries where the Gross National Income (GNI) per capita is below $3,945 in U.S. dollars. The GNI per capita of middle income countries is above $3,946 and below $12,195. The GNI per capita of high income countries is above $12,195.

within countries (Rabe-Hesketh and Skrondal 2008). The multilevel analysis consists of an individual- and a country-level model. At the individual-level, the general form of the models for a student *i* in country *j* can be written as,

$$\eta_{ij} = \beta_{0j} + \beta_{1j}(Family\ SES)_{ij} + \sum_{2}^{k} \beta_{kj} X_{kij} + r_{ij} \tag{1}$$

The left-hand side link functions η_{ij} are treated differently for binary and continuous outcome variables. For the binary dependent variable—*use of educational software at home*—η_{ij} can be specified as:

$$\eta_{ij} = ln(\frac{\emptyset_i}{1-\emptyset_i}),$$

where $\emptyset_i$ is equal to $P(y = 1|\boldsymbol{X})$, making the model a multilevel logistic model. For the continuous dependent variable—*Internet literacy*—η_{ij} is equal to y. β_{0j} is the individual-level intercept, adjusted for family SES and other individual-level control variables. β_{1j} is the coefficient of family SES. r_{ij} is the unexplained variance for individual *i* in country *j*. At the country-level, I assume:

$$\beta_{0j} = \gamma_{00} + \sum_{1}^{k} \gamma_{0k} Z_{kj} + \mu_{0j} \tag{2}$$

$$\beta_{1j} = \gamma_{10} + \sum_{1}^{k} \gamma_{1k} Z_{kj} + \mu_{1j} \tag{3}$$

where the intercept and the coefficient to family SES slope are allowed to randomly vary across nations. Z_{1j} to Z_{kj} indicate a set of country-level variables. All continuous country-level variables are centered at the grand mean, so that γ_{00} represents the grand mean of the intercept and γ_{10} indicates the grand mean of the family SES slope for countries whose country-level variables are set at the average values. The main focus of this chapter is to examine the effects of

national contextual factors on the digital divide, measured as the slope of family SES (Equation 3).

The analyses in this chapter proceed in three stages. In the first stage, I use logit and linear regressions respectively for *educational software use at home* and *Internet literacy* and estimate the models separately in each of the 55 countries. Based on these models, I use graphs to visualize how the impact of family SES on the two digital use measures varies across countries of different economic standings. Next, I use multilevel models to formally examine the country-level variation in digital divide. To test the hypotheses that economic development, democraticness, R&D investment, and secondary educational expenditures reduce the level of digital learning inequality, I estimate the effects of country-level factors on the two dependent variables and the slopes of family SES. Finally, I examine whether the effects of R&D investment and secondary educational expenditures on the family SES slopes differ across low-, middle-, and high-income countries. Based on the estimated models, I calculate the predicted SES slopes for the 55 countries and present the results in graphs.

4.5 Results

4.5.1 Examining the Effect of Family SES on Digital Learning

Figure 4.1 illustrates the variations in the inequalities of digital learning divide (more specifically, the relationship between family SES and the two outcome measures for digital skills and usage) across three country-level income groups using the results of separate regression models for each country. Overall, the effects of family SES on the two outcomes differ substantially across national income level. On average, the slopes of family SES among low-income countries are steeper than the slopes in most middle- and high-income countries. This suggests poor countries have higher levels of the digital divide. However, I also see that the

slopes of family SES vary among countries with similar wealth, particularly within high-income countries. This suggests that economic development can only partially explain cross-national variation in the level of digital learning inequality.

[Figure 4.1 about Here]

Using multilevel modeling, I more formally examine the country-level variation in the inequalities of digital learning in Table 4.2. Model 1 shows the average effect of family SES on the use of educational software at home in all nations. For each standard deviation increase in family SES, the odds of using educational software at home increase by a factor of 2.28 ($=e^{.823}$, $p<.01$). Because the same odds ratio coefficient may indicate a small probability change if the original odds are small (e.g., $\Pr(y=1)=0.1$, leading to an odds of 1/10), and a large probability change if the original odds are even among the two outcome choices (e.g., $\Pr(y=1)=0.5$, leading to an odds of 1), we should also note that, as shown in Table 4.1, approximately 49 percent of respondents in the PISA sample used educational software at home. This suggests that the association between family SES and the use of educational software at home is not only significant, but also substantial in magnitude. In Model 1, I also see that the country-level variance in family SES is .056. This suggests a 95% confidence interval ranging from .358 to 1.288 for the SES coefficients. In substantive terms, this means that, excluding the extreme 5% of the two sides, the odds ratio effects of one standard deviation change in family SES range from 1.43 (or increase 43%; i.e., $[e^{.358}-1]\times 100\%$) to 3.63 times (or increase 263%). These findings suggest a sizable variation in levels of the digital divide in educational software use at home across the 55 nations.

[Table 4.2 about Here]

Model 2 includes individual-level control variables. The estimated average effect of family SES decreases only slightly and remains statistically significant (β=.807, p<.01). A one standard deviation increase in family SES increases the odds of educational software use at home by a factor of 2.24. Thus, after accounting for a variety of individual characteristics, the effect of family SES on the odds of a student having educational software at home remains substantial. Again, results from the variance components indicate that the 95% confidence interval range of the SES slope is between .350 and 1.264, indicating that the odds ratio effect of one standard deviation change in family SES ranges from 42% to 254% across all countries.

Model 3 presents the average effect of family SES on Internet literacy. For each standard deviation increase in family SES, Internet literacy increases by .338 standard deviations (p<.01). After including other individual-level characteristics in Model 4, the coefficient for family SES decreases slightly to .332. When taking variance components into account, I find that the impact of family SES on Internet literacy ranges between .091 and .573 standard deviations among 95% of the countries included in my analysis.[11] Taken together, I conclude that both educational software use at home and Internet literacy are significantly affected by family SES, but the size of the SES effect varies substantially across countries.

Most of the individual-level controls, as shown in Models 2 and 4, perform as expected. Students attending a higher school grade than average are more likely to use educational software at home and have higher Internet literacy, as are those from immigrant versus non-immigrant families. Speaking a foreign language at home does not significantly impact

[11] The interclass correlation coefficient (ICC) for the empty model (i.e., a model that only includes the intercept) predicting the use of educational software at home is .127. This means that about 13% of the variation in the intercept is due to country-level differences. For Internet literacy, about 11% of the variation in the intercept occurs at the country level. While informative, these numbers do not represent the cross-national variation in the family SES slope—the main focus of this empirical chapter.

educational software use at home or Internet literacy. These findings suggest that when controlling for other socio-demographic characteristics, immigrant students are not disadvantaged in the use of digital technology compared to their non-immigrant peers. Compared to two-parent families, students living in single-parent families are less likely to use educational software at home but have similar levels of Internet literacy. Finally, I note that male students have significantly higher Internet literacy than females, which is consistent with previous studies that have found a tendency for girls to report lower self-assessment of online skills than boys (Hargittai and Shafer 2006). Despite this gender gap in Internet literacy that advantages boys, Table 4.2 also shows that male students are less likely to report using educational software at home than females. This result corresponds with findings from recent studies that despite their high rates of computer use, male students are more likely than female students to use computers for non-educational activities, such as gaming (Imhof, Vollmeyer, and Beierlein 2007).

4.5.2 Sources of Cross-National Variation in the Inequalities of Digital Learning

To evaluate key determinants of the digital learning inequality between students, I estimate multilevel models assessing the effects of country-level variables on both the two outcomes and the slope of family SES. In Table 4.3, I first include GDP per capita and composite polity score (Model 1 for educational software use at home; Model 4 for Internet literacy). I then test if R&D and secondary educational expenditures as a percent of GDP affect the digital divide in use of educational software at home (Models 2 and 3) and Internet literacy (Models 5 and 6).[12] All analyses include the same individual-level control variables shown in Table 4.2. The top half of Table 4.3 shows the effects of country-level measures on the intercept. The bottom half of the

[12] In supplementary analyses including both R&D and educational expenditures, the significant effect of R&D disappears because of the high correlation between the two variables (r=.48), but the general patterns remain the same.

table examines the effects of country-level variables on the slope of family SES (or, in other words, the level of digital learning inequality along the socioeconomic line). The differential effects of family SES by R&D and secondary educational expenditures across country-level income groups are further examined in Table 4.4.

[Tables 4.3 about Here]

Beginning with educational software use at home in Model 1, I see that the average effect of family SES is .806. This suggests that one standard deviation change in family SES increases the odds of educational software use at home by a factor of 2.24. The coefficients for GDP per capita in the intercept and the family SES slope equations are respectively .702 and −.191. This suggests that economic development increases student use of educational software at home and, at the same time, reduces the digital divide between lower- and higher-SES students. More specifically, for every unit increase in the natural log of GDP per capita, the odds of educational software use at home increases by 102% ($e^{.702}$), and the odds ratio effects for every standard deviation of family SES decrease by 17%, from $e^{.806}$ to $e^{.615}$. The polity score has no significant effect on the rate of educational software use at home or the slope of family SES (p>.1). Together, these findings confirm that economic development outweighs political freedom when explaining the digital divide (Robison and Crenshaw 2010).

Model 2 considers the effect of R&D, controlling for GDP per capita and composite polity score. I find that increasing national investment in R&D does not affect educational software use at home, but reduces the digital gap by SES. The magnitude of the effect is moderate, with a log unit increase in R&D leading to a 7% decrease in the standardized effect of family SES in odds ratios. Model 3 shows that students living in countries with higher secondary education expenditures are more likely to use educational software at home (b=.610, p<.05).

More importantly, the effect of secondary educational expenditures in reducing the digital divide is both statistically significant and substantial in size, with a one unit change in the measure leading to a 19% decrease of the family SES effect. To place this in the context of my data, this effect is equivalent to the ratio of educational expenditures of the countries ranked in the highest 90% of educational expenditures (approximately 2.76% of GDP) to the countries ranked in the lowest 10% of educational expenditures (approximately 1.04%).

Models 4, 5, and 6 examine the effects of country-level variables on Internet literacy. In Model 4, a one standard deviation increase in family SES increases Internet literacy by .332 standard deviations, holding individual level variables constant. GDP per capita increases students' Internet literacy (b=.181, p<.05) and reduces the Internet literacy gap by family SES (b=−.134, p<.01). The polity score does not impact Internet literacy or the slope of family SES. Model 5 shows that R&D does not have a significant effect on Internet literacy, but significantly reduces the digital divide in Internet literacy (b=−.029, p<.01). In Model 6, secondary educational expenditures as a percent of GDP does not have a significant relationship with Internet literacy or the digital gap in Internet literacy.

Overall, the results in Table 4.3 suggest that economic development is a powerful predictor of digital learning inequality for teenage students. Net of economic and political factors, investments in R&D and secondary education are associated with reductions in the digital divide, though the effects of educational expenditures are limited to the use of educational software at home. However, these general patterns may vary across different levels of national economic development—a possibility I examine next.

4.5.3 Differential Effects between Rich and Poor Countries

Table 4.4 reports the differential effects of R&D investment and secondary education

expenditures on the digital learning inequalities between low-, middle-, and high-income countries. Based on the two corollaries discussed earlier, I focus on the interaction effects between the key independent variables and the level of economic development on the slope of family SES. I see two notable interaction effects. First, Model 1 shows that the negative impact of R&D as a percent of GDP on the relationship between family SES and educational software use at home is greater in size in low-income countries (b=−.180, p<.01) than in high-income countries. Second, Model 4 suggests that the higher the national income, the greater the negative impact of secondary educational expenditures on the inequality in Internet literacy (b=.306 for low-income countries; b=.145 for middle-income countries).

[Tables 4.3 about Here]

To further examine the patterns of the above differential effects, I plot the predicted slopes of family SES by level of national income in Figure 4.2. Each graph presents the effect of country-level factors (x-axis) on the level of the digital divide (i.e., family SES slope). Beginning with educational software use at home (the left panel), I find a strong negative relationship between R&D and the SES slope for low- and middle-income countries, but not for high-income countries. This finding suggests that investment in R&D can play an important role in reducing digital learning inequality in lower income countries, but it offers little advantage in high-income countries. I should note that low-income countries' R&D investments as a percent of GDP are smaller than most high-income countries. This leaves a lot of room for R&D growth and hence reduction of the digital divide for these countries. On the contrary, the relatively small effect found in high-income countries suggests there may be a ceiling above which further R&D spending is no longer helpful in reducing digital inequality. I also find a large and significant negative effect for secondary educational expenditures on the digital divide, and the pattern of

this relationship is similar across countries regardless of their levels of economic development. This finding suggests that educational expenditures play a role in reducing the digital divide in software use at home in all countries, regardless of national wealth.

[Figure 4.2 about Here]

Moving to Internet literacy, I also find notably different effects for SES among countries with different levels of national income. Overall, this finding supports Hypothesis 4.3a which states that higher levels of national income are associated with stronger effects of R&D and educational expenditures in bridging the digital divide. First, increased R&D spending is associated with a decline in the effect of SES among high-income countries, but not in low- or middle-income countries.[13] This may be due in part to a lack of Internet access in lower income countries. This lack of access can restrict the role of R&D in bridging the digital divide in Internet literacy. Second, the negative relationship between educational expenditures and the effect of SES exists only in high-income countries while the effect actually becomes positive when looking at low-income countries. In other words, increased educational expenditures are associated with a widening digital divide among poor nations. This counterintuitive finding begs a question: why don't educational expenditures lead to greater equality in digital literacy for students in low-income countries?

I consider several possible answers to this question through a series of supplementary analyses. First, because of the small number of countries, it is possible that the patterns for low-income countries observed in Figure 4.2 are sensitive to the categorization of countries. To test

[13] Trinidad & Tobago and Macao are potential outliers in Figure 4.2 with regard to the effect of R&D for high-income nations. Supplementary analyses excluding these two countries show patterns consistent with those reported here.

the robustness of the finding, I repeat the same analyses in Table 4.4 and Figure 4.2 using an alternative classification of country-level income groups (ITU 2011:27).[14] The conclusion remains consistent.

Second, it is possible that the high class inequality in less-developed nations may contribute to the widening digital divide. To account for the possible effects of income inequality on digital learning inequality, I run supplemental analyses including the Gini index as a covariate and the results remain unchanged. Finally, I consider the possibility that rates of secondary educational enrollment are associated with the level of digital inequality in Internet literacy.[15] I find that higher enrollment rates are associated with greater inequality among less-developed countries, but enrollment rates have no effect in developed countries. This further supports the possibility that national efforts to promote educational opportunity—either by increasing educational expenditures or expanding school enrollments—may not necessarily reduce the inequality in Internet literacy between affluent and poor students. Together, the results of these analyses suggest that the benefits of increased educational spending are disproportionately enjoyed by socioeconomically advantaged students in low-income countries, regardless of class inequality and educational enrollment rates.

To summarize, the analyses in Table 4.3 show that economic development, R&D investments, and educational expenditures have significant effects on reducing the digital inequality among teenage students. Table 4.4 and Figure 4.2 further indicate significant differences in the effect of national investments in R&D and educational expenditures in bridging the digital gap across countries with various income levels. Consistent with previous

[14] Based on ITU, there are 8 low-income countries, 18 middle-income countries, and 29 high-income countries.
[15] The Gini index data are obtained from the World Income Inequality Database (UNU-WIDER 2008). Secondary education enrollment rates are derived from the World Bank (2015a).

literature that questions the role of educational expansion in reducing educational inequalities (Hannum and Buchmann 2005; Juárez and Gayet 2014), findings indicate that, among less-developed countries, the benefits of increased educational expenditures may be limited to just the most affluent students; in contrast, increased educational spending in developed countries is more beneficial to less-affluent students.

4.6 Discussion and Conclusion

The use of digital technology in education has continued to grow in the past decade, making digital literacy an increasingly important component of success for students around the world. Despite its growing importance for education, a digital gap in skills and usage exists between more and less affluent individuals. This disparity has come to be known as the second digital divide and been identified in a wide range of countries throughout the world (Notten et al. 2009). In spite of the wealth of research on the digital divide, the national-level factors that contribute to this disparity in education among students have received limited attention. This is surprising since scholars have long recognized the need to investigate the role of the government and public policies in the integration of e-learning into schools and education (DiMaggio et al. 2004; Erichsen and Salajan 2014; Natriello 2001). Motivated by this gap in the research as well as findings from previous studies (Norris 2001), I investigate how economic development, democraticness, and two measures of national investments—R&D investments and secondary education expenditures—are associated with the digital learning inequalities among 15-year-old students across 55 countries.

The analysis from this chapter reveals several key findings. First, extending previous research based on adult samples (Robison and Crenshaw 2010), I find GDP per capita to be a powerful predictor of the digital gap among teenage students. Despite the magnitude of this

finding, however, I note that high levels of digital inequality still persist in relatively affluent countries. This suggests that more than just economic growth is required to solve the problem of the digital divide, which leads us to the second major finding that both R&D investments and expenditures on secondary education can reduce digital learning inequality. The size of the effects for these measures are modest, but they remain statistically significant even after controlling for economic development and individual-level background characteristics. Given these findings, I surmise that targeted investments in research, innovation, and education aimed at enhancing digital learning opportunities for all students could potentially reduce digital inequality further. Policymakers interested in reducing digital inequality may want to take this finding into consideration when addressing the digital divide.

Equally important, I show that the effects of R&D and educational expenditures vary between more- and less-developed countries. Specifically, R&D spending reduces the gap in educational software use at home only in less-developed countries. This finding suggests there may be an opportunity to reduce the digital divide for these countries since they have the greatest room to expand their investments in R&D (see Appendix 4.2 for examples). Increased R&D spending and educational expenditures are associated with reducing the Internet literacy gap among high-income countries, but not in low- or middle-income countries. In fact, and perhaps surprisingly, increased expenditures on education in low-income countries leads to a widening Internet literacy gap between lower SES and higher SES students. This may be attributable to the complex interaction of several socio-economic factors such as lack of social mobility, weak labor markets, and widespread poverty in less-affluent countries. I find some evidence to support this possibility in the data. Among low-income countries, for example, Moldova has the highest level of educational expenditures in my sample, but its strikingly poor economic conditions have

further exacerbated the hardships of socioeconomically disadvantaged students (Worden 2014).

In all, I suggest that future research should explore specific projects, policies, or practices that are directly related to equipping the young generation with digital skills—especially economically disadvantaged students. Since digital technology appears likely to be a dominant force in society for the foreseeable future—affecting earnings and other social outcomes—ensuring the next generation is well-prepared with digital skills should be a priority for countries seeking to compete in the global economy. So long as a high level of inequality in these skills persists, social scientists must continue to seek out solutions by exploring various local and national investments which governments can make to help reduce digital learning inequalities.

Table 4.1: Descriptive Statistics and Variable Descriptions in the Analysis

Variable	Mean	SD	Description / Coding
Individual-level variables			
Use of educational software at home	0.49	0.50	1 = yes, 0 = no
Internet literacy	0.00	1.00	Standardized variable based on five online reading activities (Cronbach's α = .79): reading online news, using an online dictionary or encyclopedia (e.g., Wikipedia), searching online information to learn about a particular topic, taking part in online group discussions or forums, and searching for practical information online (e.g., schedules, events, tips, recipes). Response categories from lower to higher values are: "I don't know what it is", "never or almost never", "several times a month", "several times a week", and "several times a day".
Family SES	0.00	1.00	Standardized and PISA-created index of economic, social, and cultural status (OECD 2012), including: parental occupation status expressed as the index of ISEI, parental education in years, and an index of household possessions (e.g., a room for the child, possessions of classical literature, a desk for the child to study at home, the number of books at home).
Male	0.49	0.50	1 = male, 0 = female
School grade	-0.21	0.68	Measure of student progress in school. 0 represents students attending school at the same grade as most of other students of the same age within their country. A negative integer (coded -1, -2, etc.) or a positive integer (coded 1, 2, etc.) indicates students are at a grade below or above their expected grade level.
First generation immigrant	0.04	0.18	1 = yes, 0 = no. Reference group = non-immigrant student.
Second generation immigrant	0.05	0.21	1 = yes, 0 = no. Reference group = non-immigrant student.
Foreign language use at home	0.11	0.31	1 = yes, 0 = no.

Table 4.1 (*continued*)

Variable	Mean	SD	Description / Coding
Individual-level variables			
Single-parent family	0.17	0.38	1 = yes, 0 = no. Reference group = two-parent family.
Other family	0.04	0.20	1 = yes, 0 = no. Reference group = two-parent family.
Country-level variables (all natural log transformed)			
GDP per capita	3.08	0.68	Gross Domestic Product per capita in thousands of 2009 purchasing power parity (PPP) dollars.
Composite polity score	2.86	0.42	Composite variable based on two variables: democracy and autocracy. The original scale ranges from -10 (strongly autocratic) to 10 (strongly democratic). Before it is natural log transformed, all values are transferred into positive integers by adding 11.
R&D as % of GDP	-0.14	1.08	Research and Development including both public and private expenditures that cover basic research, applied research, and experimental development.
Secondary educational expenditures as % of GDP	0.56	0.40	Total government expenditures on secondary education from the local, regional, and central government and transfers from international sources.

Data Source: All individual-level variables are from the Programme for International Student Assessment (PISA) 2009; GDP per capita and R&D are compiled from the World Bank's World Development Indicators (2015c); composite polity score is from Marshall et al.'s (2010) Polity IV Project; secondary educational expenditures are from the World Bank's Education Statistics (2015a).
Note: To preserve cases, multiple imputations (m =10) for missing cases are used for individual-level control variables.

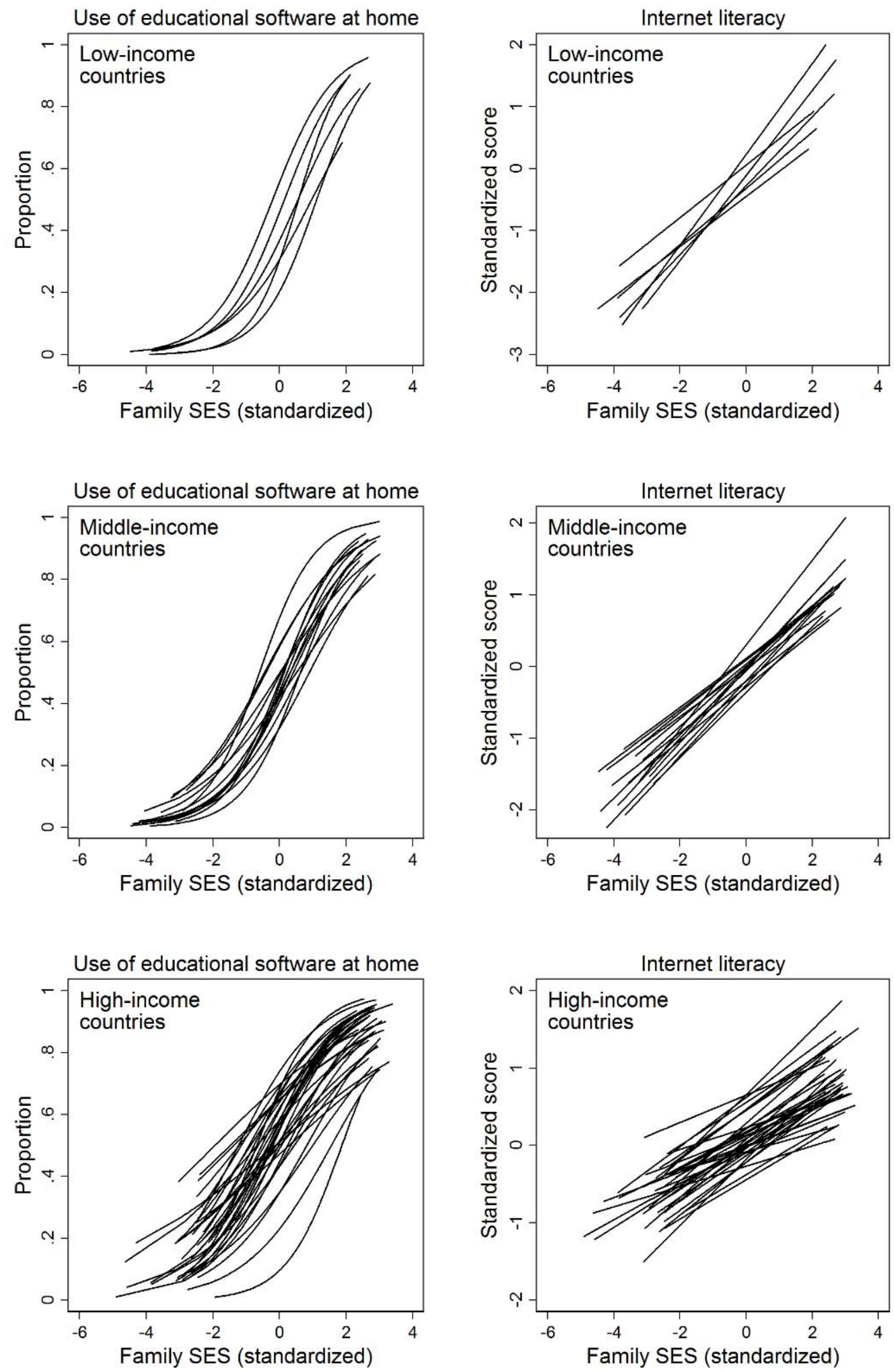


Figure 4.1: Regression Lines of Educational Software Use at Home and Internet Literacy

Note: The regression line for each country represents the bivariate relationship between family SES and each of the two dependent variables—use of educational software at home and Internet literacy.

Table 4.2: Multilevel Analyses for the Inequalities of Digital Learning with Individual-Level Variables

	Use of educational software at home[a]		Internet literacy[b]	
	Model 1	Model 2	Model 3	Model 4
Intercept	-.015 (.082)	.106 (.088)	.034 (.036)	-.003 (.038)
Family SES	.823 (.032)**	.807 (.032)**	.338 (.018)**	.332 (.017)**
Male		-.129 (.024)**		.080 (.010)**
School grade		.098 (.019)**		.098 (.008)**
First generation immigrant		.104 (.039)**		.191 (.028)**
Second generation immigrant		.219 (.053)**		.207 (.026)**
Foreign language use at home		-.070 (.047)		-.027 (.038)
Single-parent family		-.215 (.016)**		.007 (.006)
Other family		-.206 (.038)**		-.042 (.019)*
Variance components				
Between-country intercept variance	.364	.367	.072	.072
Between-country family SES variance	.056	.054	.017	.015
Within-country variance			.813	.806
Log-likelihood	-553,994	-554,401	-524,719	-523,062
$N_{\text{Individual-level}}$	391,261	391,261	398,681	398,681

Note: Number of countries = 55. Robust standard errors are in parentheses. All coefficients are adjusted by multiple imputations for missing cases in the control variables (m = 10). *Log-likelihood* is from imputed dataset m = 1. [a] For an intercept-only model: between-country intercept variance is .479. The intraclass correlation (ICC) is .127. [b] For an intercept-only model: between-country intercept variance is .117. Within-country variance is .913. ICC is .114.

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

Table 4.3: Multilevel Analyses for the Inequalities of Digital Learning with Country-Level Variables

	Use of educational software at home			Internet literacy		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Effects on the Intercept						
Intercept	.106 (.088)	.106 (.088)	.106 (.084)	-.008 (.043)	-.008 (.043)	-.008 (.042)
GDP per capita	.702 (.113)**	.687 (.102)**	.614 (.105)**	.181 (.068)*	.158 (.076)*	.153 (.066)*
Composite polity score	.091 (.110)	.080 (.112)	-.148 (.188)	.013 (.087)	-.003 (.088)	-.061 (.122)
R&D as % of GDP		.019 (.097)			.029 (.036)	
Secondary educational expenditures as % of GDP			.610 (.250)*			.190 (.126)
Effects on the Family SES Slope						
Intercept	.806 (.027)**	.806 (.026)**	.806 (.026)**	.332 (.012)**	.332 (.011)**	.332 (.012)**
GDP per capita	-.191 (.041)**	-.139 (.041)**	-.161 (.036)**	-.134 (.023)**	-.112 (.023)**	-.132 (.025)**
Composite polity score	-.021 (.036)	.016 (.046)	.059 (.050)	-.031 (.034)	-.015 (.027)	-.025 (.034)
R&D as % of GDP		-.068 (.029)*			-.029 (.010)**	
Secondary educational expenditures as % of GDP			-.205 (.059)**			-.014 (.035)
Variance components						
Between-country intercept variance	.398	.397	.352	.096	.095	.091
Between-country family SES variance	.037	.033	.032	.007	.006	.007
Within-country variance				.806	.806	.806
Log-likelihood	-554,396	-554,402	-554,395	-523,049	-523,046	-523,048
$N_{\text{Individual-level}}$	391,261	391,261	391,261	398,681	398,681	398,681

Note: Number of countries = 55. Robust standard errors are in parentheses. All coefficients are adjusted by multiple imputations for missing cases in the control variables (m = 10). *Log-likelihood* is from imputed dataset m = 1. All models include individual-level control variables (gender, school grade, immigration status, foreign language use at home, and family structure). Family SES is group mean centered. All country-level variables are natural log transformed and grand mean centered.

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

Table 4.4: Multilevel Analyses for the Inequalities of Digital Learning: Differential Effects by Country Income Group

	Use of educational software at home		Internet literacy	
	Model 1	Model 2	Model 3	Model 4
Effects on the Intercept				
Intercept	.547 (.086)**	.418 (.129)**	.142 (.060)*	.124 (.050)*
Low-income country[a]	-1.010 (.691)	-1.446 (.460)**	-.519 (.356)	-.635 (.194)**
Middle-income country[a]	-.686 (.260)*	-.411 (.389)	-.380 (.096)**	-.204 (.117)+
Composite polity score	.070 (.164)	-.242 (.226)	-.060 (.096)	-.055 (.090)
R&D as % of GDP	-.152 (.090)+		-.019 (.059)	
R&D as % of GDP × Low-income country	.569 (.404)		.033 (.230)	
R&D as % of GDP × Middle-income country	.333 (.252)		-.074 (.095)	
Secondary educational expenditures as % of GDP		.581 (.504)		.074 (.154)
Secondary educational expenditures as % of GDP × Low-income country		.366 (.655)		.395 (.210)+
Secondary educational expenditures as % of GDP × Middle-income country		-.557 (.584)		-.221 (.187)
Effects on the Family SES Slope				
Intercept	.720 (.040)**	.727 (.040)**	.279 (.011)**	.274 (.013)**
Low-income country[a]	.118 (.052)*	.330 (.128)*	.299 (.119)*	.127 (.059)*
Middle-income country[a]	.111 (.060)+	.149 (.096)	.151 (.028)**	.065 (.028)*
Composite polity score	.005 (.054)	.086 (.056)	.030 (.024)	.036 (.020)+
R&D as % of GDP	-.027 (.044)		-.039 (.008)**	
R&D as % of GDP × Low-income country	-.180 (.054)**		.074 (.070)	
R&D as % of GDP × Middle-income country	-.092 (.065)		.055 (.029)+	
Secondary educational expenditures as % of GDP		-.183 (.111)+		-.107 (.034)**
Secondary educational expenditures as % of GDP × Low-income country		.020 (.142)		.306 (.055)**
Secondary educational expenditures as % of GDP × Middle-income country		.013 (.124)		.145 (.041)**
Variance components				
Between-country intercept variance	.326	.312	.074	.068
Between-country family SES variance	.030	.032	.006	.005
Within-country variance			.806	.806
Log-likelihood	-554,415	-554,401	-523,032	-523,028
$N_{\text{Individual-level}}$	391,261	391,261	398,681	398,681

Note: Number of countries = 55. Robust standard errors are in parentheses. All coefficients are adjusted by multiple imputations for missing cases in the control variables (m = 10). *Log-likelihood* is from imputed dataset m = 1. All models include individual-level control variables (gender, school grade, immigration status, foreign language use at home, and family structure). Family SES is group mean centered. With the exception of low-income country and middle-income country, all country-level variables are natural log transformed and grand mean centered. [a] High-income country is the reference category.
** $p < .01$, * $p < .05$, + $p < .1$ (*2-tailed*).

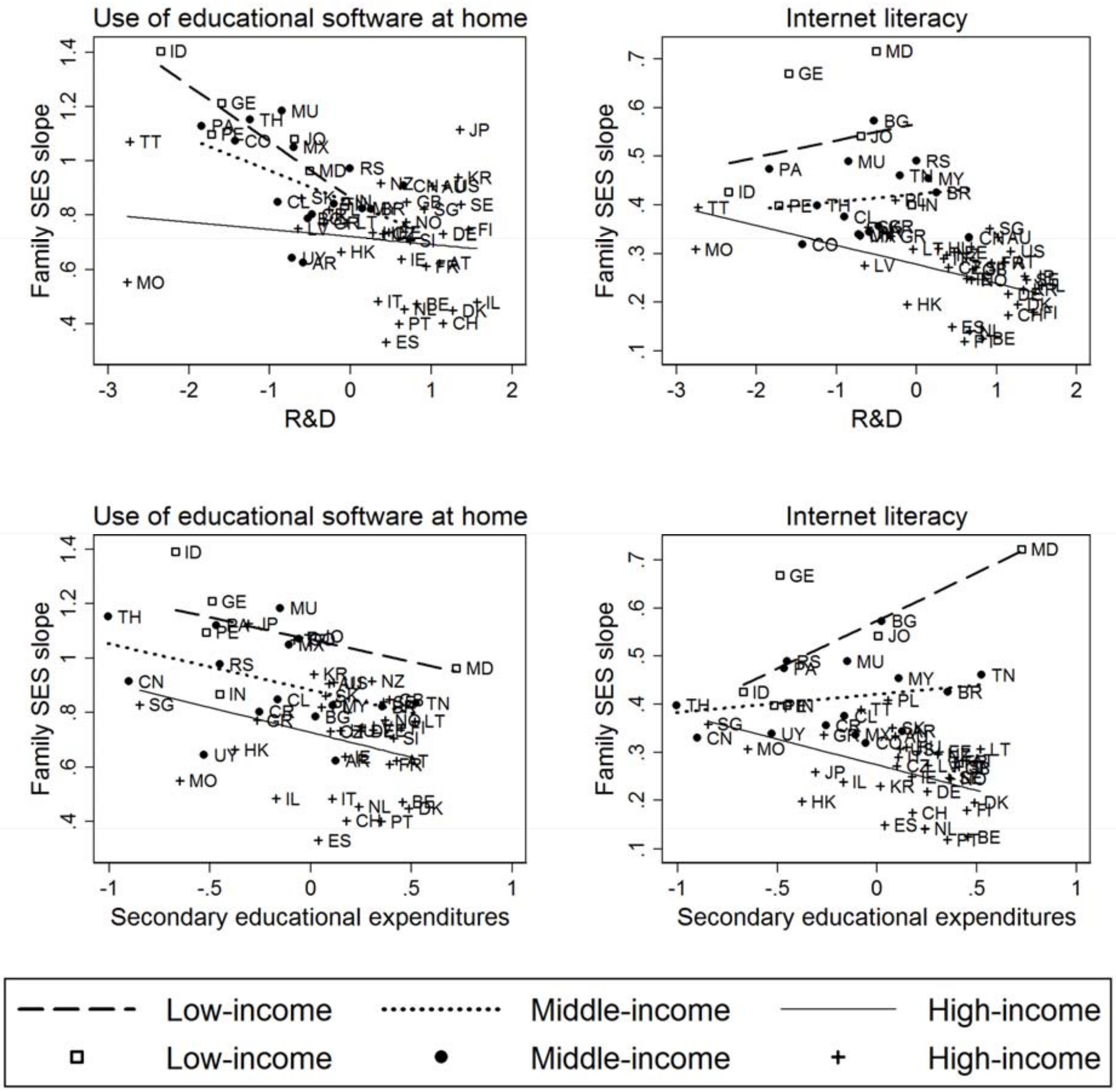


Figure 4.2: Predicted Family SES Slopes by Country Income Group

Note: Predicted family SES slopes are calculated from Table 4.4 (Model 1 in the top left corner; Model 2 in the bottom left; Model 3 in the top right; Model 4 in the bottom right). The plotted lines represent the association between the variable on the *x*-axis and the slope of family SES for low-income (dashed line), middle-income (dotted line), and high-income countries (solid line). The symbols attached to country acronyms represent the predicted family SES slopes adjusted for between-country variance. Both R&D and secondary educational expenditures, measured as % of GDP, are natural log transformed and centered at the grand mean. 0 is the mean of 55 countries. All coefficients are adjusted by multiple imputations for missing cases in the control variables (m = 10).

Appendix 4.1: Sample Size and Descriptive Statistics for Key Individual-Level Variables in 55 Countries

Country	Sample size	Use of educational software at home: Mean	SD	Internet literacy: Mean	SD	Family SES: Mean	SD
Argentina (AR)	4,774	.40	.49	-.27	.97	-.19	1.02
Australia (AU)	14,251	.70	.46	-.01	.86	.60	.66
Austria (AT)	6,590	.49	.50	.13	.87	.40	.72
Belgium (BE)	8,501	.64	.48	-.20	.81	.51	.80
Brazil (BR)	20,127	.24	.43	-.37	1.12	-.70	1.05
Bulgaria (BG)	4,507	.62	.48	.45	1.22	.23	.86
Chile (CL)	5,669	.37	.48	.00	.97	-.11	1.01
Colombia (CO)	7,921	.37	.48	-.07	.96	-.55	1.08
Costa Rica (CR)	4,578	.41	.49	-.46	.96	-.48	1.14
Czech (CZ)	6,064	.64	.48	.66	.88	.34	.64
Denmark (DK)	5,924	.73	.44	.21	.83	.44	.81
Estonia (EE)	4,727	.69	.46	.61	.86	.48	.69
Finland (FI)	5,810	.35	.48	.02	.81	.68	.68
France (FR)	4,298	.39	.49	-.02	.84	.23	.73
Georgia (GE)	4,646	.27	.44	-.03	1.14	.10	.85
Germany (DE)	4,979	.57	.49	.23	.85	.48	.79
Greece (GR)	4,969	.42	.49	.08	1.02	.35	.86
Hong Kong (HK)	4,837	.57	.49	.58	.84	-.38	.88
Hungary (HU)	4,605	.47	.50	.53	.95	.19	.82
India (IN)	4,826	.17	.38	-.90	1.27	-1.11	.96
Indonesia (ID)	5,136	.16	.36	-.77	.97	-1.00	.95
Ireland (IE)	3,937	.57	.49	-.35	.85	.38	.74
Israel (IL)	5,761	.54	.50	.26	.96	.32	.77
Italy (IT)	30,905	.54	.50	.11	1.00	.24	.85
Japan (JP)	6,088	.16	.36	-.30	.95	.32	.63
Jordan (JO)	6,486	.53	.50	-.32	1.14	-.10	.89
Korea (KR)	4,989	.60	.49	.21	.85	.21	.71
Latvia (LV)	4,502	.70	.46	.53	.89	.29	.75
Lithuania (LT)	4,528	.61	.49	.71	.95	.30	.84
Macao (MO)	5,952	.62	.49	.13	.85	-.28	.75
Malaysia (MY)	4,999	.56	.50	-.40	1.00	-.10	.77
Mauritius (MU)	4,654	.59	.49	-.16	1.09	-.25	.87
Mexico (MX)	38,250	.32	.47	-.14	.91	-.67	1.11
Moldova (MD)	5,194	.35	.48	.12	1.25	-.16	.85
Netherlands (NL)	4,760	.70	.46	-.01	.82	.60	.74
New Zealand (NZ)	4,643	.63	.48	-.09	.85	.41	.68
Norway (NO)	4,660	.68	.47	.27	.83	.74	.64
Panama (PA)	3,969	.31	.46	-.17	1.14	-.33	1.11
Peru (PE)	5,985	.31	.46	-.27	1.02	-.80	1.07
Poland (PL)	4,917	.74	.44	.71	.94	.14	.79
Portugal (PT)	6,298	.65	.48	.24	.87	.07	1.01
Serbia (RS)	5,523	.51	.50	-.06	1.08	.39	.83
Shanghai (CN)	5,115	.40	.49	-.06	.89	-.09	.91
Singapore (SG)	5,283	.64	.48	.27	.95	-.04	.70
Slovakia (SK)	4,555	.60	.49	.18	.97	.25	.73
Slovenia (SI)	6,155	.72	.45	.30	.92	.28	.76
Spain (ES)	25,887	.52	.50	.00	.87	.11	.91
Sweden (SE)	4,567	.58	.49	.13	.84	.62	.70
Switzerland (CH)	11,812	.51	.50	.06	.84	.35	.74
Thailand (TH)	6,225	.32	.47	-.28	1.04	-.69	1.09
Trinidad & Tobago (TT)	4,778	.63	.48	-.24	1.00	-.16	.82
Tunisia (TN)	4,955	.32	.47	-.55	1.15	-.74	1.13
United Kingdom (GB)	12,179	.70	.46	.10	.89	.48	.68
United States (US)	5,233	.60	.49	.00	.96	.46	.80
Uruguay (UY)	5,957	.45	.50	-.01	1.01	-.32	1.07

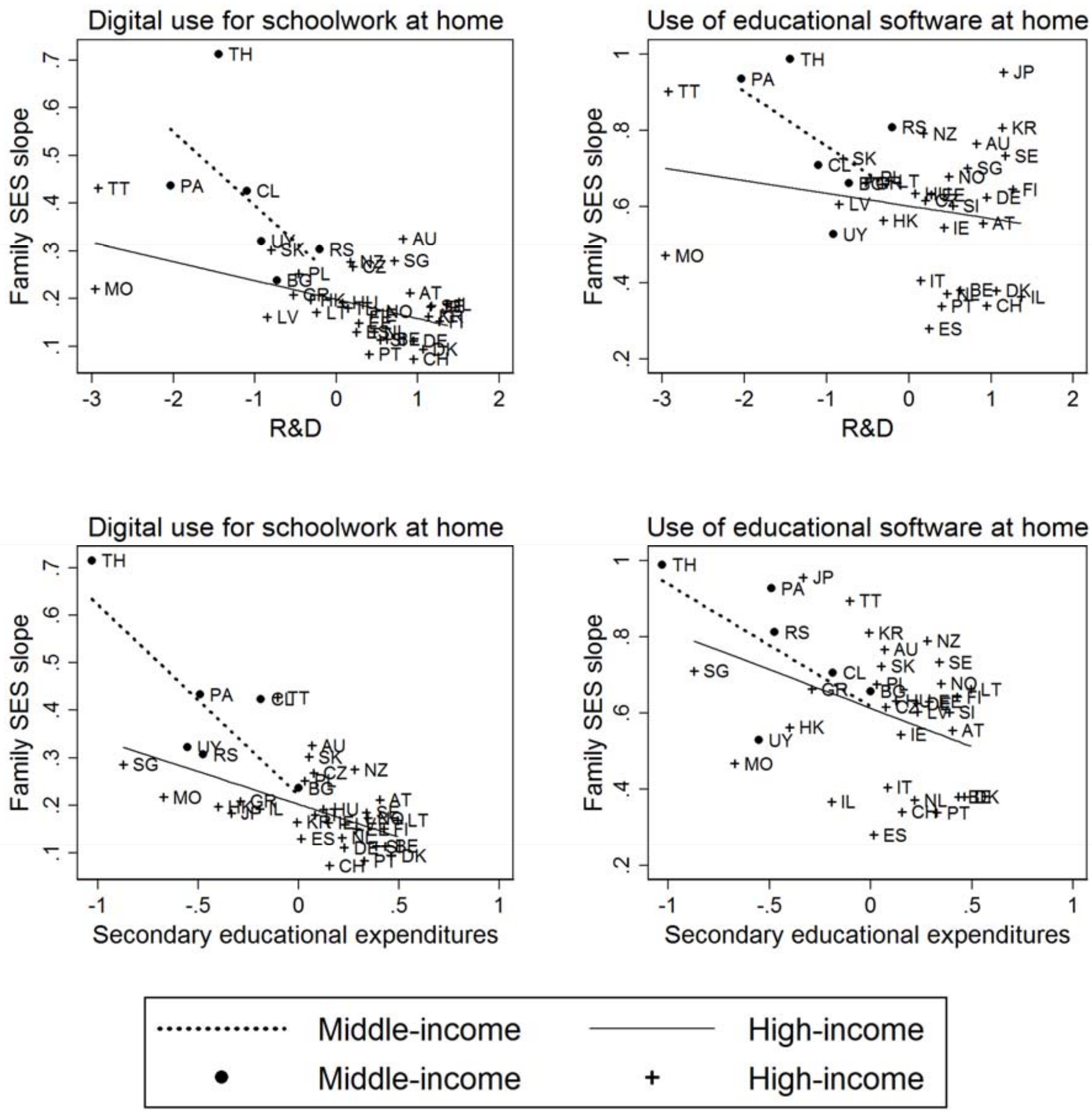
Appendix 4.2: Country-Level Variables: 55 Countries

	GDP per capita	Composite polity score	R&D as % of GDP	Secondary educational expenditures as % of GDP
Low-income countries				
Moldova (MD)	3.54	8.00	.53	3.63
India (IN)	3.96	9.00	.82	1.12
Georgia (GE)	5.46	6.00	.18	1.08
Indonesia (ID)	7.82	8.00	.08	.90
Peru (PE)	8.93	9.00	.16	1.05
Jordan (JO)	10.88	-3.00	.43	1.77
Mean	6.77	6.17	.37	1.59
Middle-income countries				
Tunisia (TN)	9.96	-4.00	.71	2.97
Shanghai (CN)	10.13	-7.00	1.68	.71
Colombia (CO)	10.26	7.00	.21	1.66
Serbia (RS)	11.81	8.00	.87	1.12
Costa Rica (CR)	11.82	10.00	.54	1.36
Thailand (TH)	12.26	4.00	.25	.64
Brazil (BR)	13.09	8.00	1.12	2.51
Mexico (MX)	13.91	8.00	.43	1.58
Panama (PA)	14.10	9.00	.14	1.10
Mauritius (MU)	14.54	10.00	.37	1.51
Argentina (AR)	14.60	8.00	.48	1.99
Bulgaria (BG)	14.88	9.00	.51	1.80
Uruguay (UY)	15.39	10.00	.42	1.04
Chile (CL)	16.23	10.00	.35	1.49
Malaysia (MY)	19.33	6.00	1.01	1.96
Mean	13.49	6.40	.61	1.56
High-income countries				
Latvia (LV)	17.04	8.00	.45	2.27
Lithuania (LT)	18.28	10.00	.83	2.95
Poland (PL)	19.15	10.00	.67	1.85
Estonia (EE)	20.21	9.00	1.40	2.40
Hungary (HU)	20.87	10.00	1.14	2.04
Slovakia (SK)	23.18	10.00	.47	1.90
Portugal (PT)	26.22	10.00	1.58	2.50
Czech (CZ)	27.02	8.00	1.30	1.94
Slovenia (SI)	27.52	10.00	1.82	2.65
Israel (IL)	27.58	10.00	4.15	1.48
Korea (KR)	28.39	8.00	3.29	1.78
Trinidad & Tobago (TT)	29.12	10.00	.06	1.62
Greece (GR)	30.44	10.00	.63	1.35
New Zealand (NZ)	30.50	10.00	1.26	2.38
Japan (JP)	31.86	10.00	3.36	1.29
Spain (ES)	32.81	10.00	1.35	1.83
Italy (IT)	34.17	10.00	1.22	1.95
France (FR)	34.81	9.00	2.21	2.60
United Kingdom (GB)	36.37	10.00	1.75	2.60
Germany (DE)	37.12	10.00	2.73	2.26
Finland (FI)	37.55	10.00	3.75	2.76

Appendix 4.2 (*continued*)

	GDP per capita	Composite polity score	R&D as % of GDP	Secondary educational expenditures as % of GDP
High-income countries				
Belgium (BE)	37.64	8.00	1.97	2.77
Denmark (DK)	39.62	10.00	3.07	2.86
Sweden (SE)	39.67	10.00	3.42	2.52
Australia (AU)	40.21	10.00	2.40	1.92
Austria (AT)	40.63	10.00	2.61	2.70
Ireland (IE)	41.88	10.00	1.63	2.09
Hong Kong (HK)	43.94	-7.00	.77	1.21
Netherlands (NL)	44.40	10.00	1.69	2.23
United States (US)	47.00	10.00	2.82	1.97
Switzerland (CH)	49.92	10.00	2.73	2.10
Norway (NO)	56.19	10.00	1.72	2.54
Singapore (SG)	61.60	-2.00	2.16	.75
Macao (MO)	76.85	-7.00	.05	.92
Mean	35.58	8.35	1.84	2.09

Note: GDP per capita is in thousands of 2009 purchasing power parity dollars. The classification of income groups is based on the World Bank (2015b). Countries within groups are sorted by GDP per capita. All of the country-level data are from 2009. For countries that have missing data on R&D as % of GDP in 2009, we use the closest available data year: Australia (2008), Georgia (2005), Jordan (2008), Mauritius (2005), Peru (2004), and Switzerland (2008). For countries that have missing data on secondary educational expenditures as % of GDP in 2009, we use the closest available data year: Costa Rica (2004), Georgia (2008), Greece (2005), Japan (2008), Macao (2000), Panama (2007), Shanghai (1999), Slovenia (2003), Tunisia (2008), and Uruguay (2006).



Appendix 4.3: Effects of R&D and Secondary Educational Expenditures on Family SES Slopes by Country Income Groups: Digital Use for Schoolwork at Home vs. Use of Educational Software at Home [a]

Note: Predicted family SES slopes are based on the same model specifications in Table 4.4 but limited to only 37 countries with valid data for the two dependent variables. [a] Standardized composite measure based on five items: 1) browsing the Internet for schoolwork, 2) using e-mail to communicate with other students about schoolwork, 3) using e-mail to communicate with teachers and for submission of schoolwork, 4) using material from the school's website, and 5) checking the school's website for announcements.

Chapter 5:

Inequality of Digital Learning Between Schools

In the previous chapter, I addressed cross-national variation in the inequalities of digital learning at the individual-level, and examined the relationship between the socioeconomic backgrounds of students and their digital learning outcomes. In this chapter, I turn to focus on school context and examine cross-national variation in the inequalities of digital learning at the school-level. Related research agendas arise as to whether schools magnify or mitigate digital learning inequality, what school-level factors determine an individual student's e-learning opportunities, and how schools influence digital inequality differently in various countries.

5.1 Problem Statement

Recent scholarship notes that access to digital technology in schools—in terms of ratio of students to computers, computer laboratories, and online networked infrastructure—has been greatly improved, particularly among developed countries (Rathbun, West, and Hausken 2003; Vigdor et al. 2014; Wells and Lewis 2006). Despite this improved access, however, disparities in digital learning *between schools* persist (OECD 2011b; UNESCO 2015). This has been called the "second digital divide" (Attewell 2001; Hargittai 2002). Most literature attributes this gap to deficiencies in school resources and teacher quality, which are often used to explain why resource-poor or underperforming schools fail to promote students' digital skills and e-learning opportunities even if access has been achieved (Natriello 2001; Warschauer 2000). However, this group of literature fails to account for how the cultural process in schools generates educational inequality (Agirdag et al. 2012; Bowles and Gintis 2002). Moving beyond the above explanation that centers on school resources or teacher quality, it is also important to address how

institutional features of schools may shape student experience in digital learning.

Moreover, recent scholarship on the digital divide in schools focuses exclusively on the experiences of rich countries, particularly the United States (Attewell 2001; DiMaggio et al. 2004; Goode 2010; Leu et al. 2014; Robinson 2014). A handful of international reports, based on descriptive statistics, show a pronounced digital gap in poor and developing countries, possibly due to structural limitations in the schools (e.g., lack of digital access) and in the countries (e.g., slow progress of Internet infrastructure) (for instance, see OECD 2011b; UNESCO 2015). While these studies are informative, we still lack a general understanding of why the relationship between access to digital technology in schools and the availability of digital learning opportunities varies cross-nationally, and whether the potential benefits accruing from the adoption of digital technology within educational settings differ by national context.

To help fill the gaps in the literature, I examine the inequalities of digital learning between schools with different socioeconomic profiles, by looking at 15-year-olds across 42 countries. This is based on a large body of literature documenting the role of the socioeconomic composition of schools in the formation of school environment, reflecting on how school principals and teachers implement different pedagogies and expectations among students from various socioeconomic status (SES) groups (Agirdag et al. 2012; Binder et al. 2016; Bowles and Gintis 2002; Coleman 1987; Entwisle et al. 2005; Jack 2016). I focus on two types of inequalities in digital learning opportunities: the gaps in 1) the use of digital technology for schoolwork at home and 2) the use of the Internet to search for information and seek knowledge.

This chapter centers on three research questions:

1. How do digital-learning opportunities vary between schools, considering both higher-SES and lower-SES schools?

2. How do the inequalities in digital learning between schools vary systematically between countries?
3. Does the use of digital technology at school promote digital learning, and how does the relationship differs between schools and vary cross-nationally?

Related to the first research question, I argue that schools that serve predominantly lower SES students are disadvantaged for digital learning opportunities, even when controlling for educational resources and school quality; this warrants more scholarly attention. Based on this rationale, I propose the following hypothesis:

Hypothesis 5.1: Students in higher-SES schools have more digital learning opportunities than those in lower-SES schools, and this gap remains statistically significant even when we control for the availability of digital learning opportunities and educational resources at schools.

The second research question asks how the inequalities in digital learning between schools vary systematically between countries. To account for the influence of national contexts, I examine a wide array of factors, which include 1) economic development (Chudgar and Luschei 2009; Gamoran and Long 2006; Hargittai 1999; Norris 2001; Robison and Crenshaw 2010), 2) income inequality (Chiu and Khoo 2005; Chudgar and Luschei 2009; Martin and Robinson 2007; Ono and Zavodny 2007; Wilkinson and Pickett 2009), 3) public expenditures on secondary education (Chiu 2010; Mayer 2001; Murray, Evans, and Schwab 1998; Raudenbush and Eschmann 2015; Vegas and Coffin 2015), and 4) investment in research and development (R&D) (Dale 2005; Drori 2006, 2010; Hanson 2006; Norris 2001; Powell and Snellman 2004). I argue that these country-level characteristics shape the digital learning inequality of 15-year-old students in a country. The theory related to these country-level characteristics was discussed

previously in Chapter 2. Based on the theory, I expect that:

> *Hypothesis 5.2: The degree of* inequality in digital learning between schools *is 1) negatively associated with national income; 2) positively associated with national income inequality; 3) negatively associated with national expenditures on secondary education; and 4) negatively associated with national investment in R&D.*

The third and final research question explores whether the use of digital technology at school reduce or reproduce existing inequalities in digital learning—a question that reflects recent scholarship questioning the need for school investment in digital technology and its potential impact on students (e.g., Natriello 2001; Vigdor et al. 2014). Given the fact that students from higher-SES schools have more digital learning opportunities in school than those from lower-SES schools, I specifically examine whether the increasing use of digital technology in the classroom reduces the relative advantage of attending a higher-SES school. As explained in Chapter 2, the presence of digital technology at a school positively predicts the use of digital learning as well as Internet literacy, but the strength of this relationship may differ across schools and vary cross-nationally. In order to test two theoretical perspectives—the marginal utility hypothesis versus the complementary process hypothesis (Chiu 2010; Schiller et al. 2002; for more information, see 2.4.2 in Chapter 2)—I form the following sets of hypotheses:

> *Hypothesis 5.3: The effect of digital use at school on digital learning is positive. But in poor countries, the size of this effect is stronger for students attending low-SES schools than those in high-SES schools (the marginal utility hypothesis). In rich countries, on the other hand, the effect size is stronger for students attending high-SES schools than those in low-SES schools (the complementary process*

hypothesis).

5.2 Data

There are notable differences in the use of the dataset between this chapter and Chapter 4. First, I added school-level data from PISA 2009, which were not included in Chapter 4, into the analyses of this chapter. Second, Chapter 4 is mainly based on responses to the main questionnaire of PISA 2009, in which 73 countries or economies participated. In this chapter, I added variables from the Information and Communication Technology Familiarity Questionnaire of PISA 2009, in which only 45 countries or economies participated. Because certain data were missing from the country-level variables, I further restricted my analysis to 42 countries.[16] The original sample size of students across 42 countries is 280,333 from 10,616 schools. I removed schools with less than 5 respondents from the analyses. Dropping missing cases from the dependent variables and the key independent variable lead to a final sample size of 275,810 individual students across 10,235 schools.

5.3 Measures

5.3.1 Dependent Variables

The main purpose of this chapter is to examine the inequalities of digital learning at the school level. I use two dependent variables to measure digital learning inequalities. The first dependent variable, *digital use for schoolwork at home,* is a composite score containing five activities at home (α=.79): browsing the Internet for schoolwork, using e-mail to communicate with other students about schoolwork, using e-mail to communicate with teachers and submit schoolwork, using material from the school website, and checking the school website for

[16] The three countries or economies not included in this chapter are: Liechtenstein, Macao, and Qatar.

announcement. Each component represents a particular aspect of online usage at home that directly relates to school-related work.

The second dependent variable, *Internet literacy*, is a composite scale measuring how often students engage in the following five online reading activities (α=.78): reading online news, using an online dictionary or encyclopedia (e.g., Wikipedia), searching online information to learn about a particular topic, taking part in online group discussions or forums, and searching for practical information online (e.g., schedules, events, tips, recipes).[17] Each component represents a particular aspect of online reading habits and the associated skills. A combination of these items indicates how familiar students are with reading text on the screen, sharing information and exchanging ideas, and interacting with others in a digital context. To ease interpretation of the results, both dependent variables are standardized with a mean of 0 and a standard deviation of 1.

5.3.2 Student-Level Independent Variables

The key independent variable, *digital use at school*, is a composite variable based on how often students are involved in nine activities at school (α=.85): chatting online, using e-mail, browsing the Internet for schoolwork, using material from the school website, posting schoolwork on the school website, playing simulations, practicing and drilling, doing individual homework on a computer, and using school computers for group work and communicating with other students. A combination of these items represent the level of student involvement in ICT related tasks at school (OECD 2012:303). Again, the variable is standardized with a mean of 0 and a standard deviation of 1.

[17] In the questionnaire, there were seven online reading activities. I exclude two of these activities—reading emails and chatting online—as they are not directly related to searching for information or acquiring knowledge.

In addition, I include several individual-level control variables. *Family SES* is a PISA-created index of Economic, Social, and Cultural Status (OECD 2012), which contains three components: parental occupation status expressed as the index of the international socio-economic index of occupation status (ISEI) (Ganzeboom et al. 1992), parental education in years, and an index of household possessions (e.g., having a room for the child, owning classical literature, having a desk for the child to study at home, and owning a number of books at home). This variable is standardized with a mean of 0 and a standard deviation of 1. *Gender* controls for the potential digital gap between male and female students (male=1). Because PISA samples 15-year-old students regardless of the grade they attend, I control for *school grade*. Students attending school at the same grade as most other students of the same age within their country are coded as 0. A negative integer (-1, -2, etc.) or a positive integer (1, 2, etc.) indicates the number of years students are either below or above their expected grade level. To control for the impact of immigration status, I include two dummy variables—*first generation immigrant* and *second generation immigration*—with *non-immigrant student* as the reference category. To control for differences in language used by immigrant students, I include a dummy variable—*foreign language use at home*—with *use the same language at home as in school* as the reference category. Lastly, I include two dummy variables—*single-parent family* and *other family*—with *two-parent family* as the reference category, to control for family structure.

5.3.3 School-Level Independent Variables

The key independent variable, *school SES mean*, is an average of the student-reported family SES for each school, used to address the impact of the socioeconomic composition of the schools. I use this variable to examine the degree of digital learning inequality at the school-level (i.e., the effect of *school SES mean* on the two dependent variables).

I also include further school-level control variables, which are derived from the PISA 2009 questionnaires for each of the schools, which are completed by school principals. To control for the difference between rural schools and schools in urban areas, I include two dummy variables—*rural* and *town*—with *city* as the reference category. To control for the time and attention that teachers give to individual students, I use the variable *class size*, which is the average class size of the language of instruction calculated from students' self-reports (OECD 2010a:82). In the questionnaire, students were asked, "on average, about how many students attend your <test language> class?" To account for the effect of teacher attributes, I include *teacher shortage*, a PISA-created index indicating the lack of teachers in four fields (α=.87): science teachers, mathematics teachers, qualified language teachers, and qualified teachers of other subjects. Original response categories, from lower to higher values, are: "not at all", "very little, "to some extent", "and "a lot". To control for a school's overall educational resource quality, I use another PISA-created index, *school resource quality*, which measures the shortage or inadequacy of seven items (α=.87): science laboratory equipment, instructional material (e.g., textbooks), computers for instruction, Internet connectivity, computer software for instruction, library materials, and audio-visual resources.

5.3.4 Country-Level Independent Variables

To examine cross-national differences in the level of the digital divide between schools, I compile a set of country-level factors from various publicly available sources. To measure a country's economic standing, I use *Gross National Income (GNI) per capita,* in thousands of 2009-purchasing-power-parity (PPP) dollars, obtained from the World Bank's World Development Indicators (2015c). To represent a country's level of income inequality, I use the *Gini index*, compiled by UNU-WIDER (2008) World Income Inequality Database. It ranges

from 0 to 1, with 0 representing perfect equality, and 1 indicating perfect inequality. To represent a country's investment in R&D and secondary education, I include *Secondary educational expenditures as a percentage of GDP* from the World Bank's Education Statistics (2015a) and *R&D as a percentage of GDP* from the World Bank's World Development Indicators (2015c). All of the country-level data are from 2009—the year that the individual-level PISA data were collected.[18] Natural log values are used for all country-level variables to account for the skewness of the distributions (Ruiter and van Tubergen 2009) and to address potential curvilinear relationships (Heisig 2011). Table 5.1 presents the descriptive statistics and coding for all the variables used in the analyses.

[Table 5.1 about Here]

5.4 Analytical Strategy and Statistical Methods

The analyses in this chapter proceed in three stages. The first stage focuses on individual-level and school-level determinants of digital learning. I begin by using two-level multilevel modeling for *digital use for schoolwork at home* and *Internet literacy* and estimate the models separately for each of the 42 countries. Each model includes an individual-level and a school-level model. Based on these models, I use graphs to visualize how the impact of school SES on the two digital learning outcomes varies cross-nationally (see the part on Figure 5.1 in Results). To more formally examine if the effect of the average of school SES outweighs other school-level characteristics, I then turn to using three-level random-intercept models to account for individual-, school-, and country-level variances (see the part on Table 5.2 in Results). The general form of the models for a student i at school s in country j can be written as,

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[18] For countries that are missing data on certain country-level variables in 2009, I utilize data from the closest adjacent year in which data is available (see Appendix 5.2).

$$Y_{isj} = \pi_{0sj} + \sum_1^k \pi_{ksj} a_{isj} + e_{isj} \quad (1)$$

$$\pi_{0sj} = \beta_{00j} + \beta_{01j}(School\ SES)_{sj} + \sum_2^k \beta_{0kj} X_{sj} + r_{0sj} \quad (2)$$

$$\beta_{00j} = \gamma_{000} + \mu_{00j} \quad (3)$$

At the individual-level (Equation 1), *Y* is the continuous dependent variable—*digital use for schoolwork at home* or *Internet literacy*. π_{0sj} is the individual-level intercept, adjusted for a set of individual-level independent variables (a_{1sj} to a_{ksj}). e_{isj} is the unexplained variance for individual *i* at school *s* in country *j*. At the school-level (Equation 2), I assume that the intercept (π_{0sj}) adjusted for school SES and other school-level control variables (X_{2j} to X_{kj}), is allowed to randomly vary across schools (r_{0sj}). All continuous school-level variables are centered at the grand mean, so that β_{00j} represents the grand mean of the intercept for schools whose school-level variables are set at the average values. At the country-level (Equation 3), I allow the intercept to randomly vary across countries (μ_{00j}).

In the second stage (see the part on Table 5.3 in Results), I use three-level random-slope modeling, where the general form of the models can be written as,

$$Y_{isj} = \pi_{0sj} + \sum_1^k \pi_{ksj} a_{isj} + e_{isj} \quad (4)$$

$$\pi_{0sj} = \beta_{00j} + \beta_{01j}(School\ SES)_{sj} + \sum_2^k \beta_{0kj} X_{sj} + r_{0sj} \quad (5)$$

$$\beta_{00j} = \gamma_{000} + \sum_1^k \gamma_{00k} W_j + \mu_{00j} \quad (6)$$

$$\beta_{01j} = \gamma_{010} + \sum_1^k \gamma_{01k} W_j + \mu_{01j} \quad (7)$$

The main focus of this part is the effects of national contextual factors on the between-

school digital divide, measured as the slope of school SES (Equation 7). W_{1j} to W_{kj} indicate a set of country-level variables. Both the intercept (β_{00j}) and the coefficient to school SES (β_{01j}) are allowed to randomly vary across nations (μ_{00j} and μ_{01j}). All continuous country-level variables are centered at the grand mean, so that γ_{000} represents the grand mean of the intercept and γ_{010} indicates the grand mean of the school SES slope for countries whose country-level variables are set at the average values.

The third and last stage examines how the effect of *digital use at school* at the individual-level differs between schools and varies across countries. I begin with using two-level multilevel modeling for *digital use at school* to estimate the models separately in each of the 42 countries, and visualizing how the effect of school SES on digital use at school varies by country (see the part on Figure 5.2 in Results). I then turn to use three-level random-slope models to formally account for school-level and country-level effects. The general form of the models can be written as,

$$Y_{isj} = \pi_{0sj} + \pi_{1sj}(Digital\ use\ at\ school)_{isj} + \sum_{2}^{k} \pi_{ksj} a_{isj} + e_{isj} \tag{8}$$

$$\pi_{0sj} = \beta_{00j} + \beta_{01j}(School\ SES)_{sj} + \sum_{2}^{k} \beta_{0kj} X_{sj} + r_{0sj} \tag{9}$$

$$\pi_{1sj} = \beta_{10j} + \beta_{11j}(School\ SES)_{sj} + \sum_{2}^{k} \beta_{1kj} X_{sj} + r_{1sj} \tag{10}$$

$$\beta_{00j} = \gamma_{000} + \gamma_{001}(GNI\ per\ capita)_{j} + \mu_{00j} \tag{11}$$

$$\beta_{01j} = \gamma_{010} + \gamma_{011}(GNI\ per\ capita)_{j} + \mu_{01j} \tag{12}$$

$$\beta_{10j} = \gamma_{100} + \gamma_{101}(GNI\ per\ capita)_{j} + \mu_{10j} \tag{13}$$

$$\beta_{11j} = \gamma_{110} + \gamma_{111}(GNI\ per\ capita)_{j} + \mu_{11j} \tag{14}$$

Equation 8 represents effects at the individual-level. The focus is how the slope of *digital use at school* (π_{1sj}) is adjusted by *school SES* when controlling for other school-level variables (X_{2j} to X_{kj}) in Equation 10, and how the cross-level interaction effect (β_{11j}) between *digital use at school* and *school SES* is shaped by GNI per capita (γ_{111}) in Equation 14. In order to ease interpretation, I calculate both the predicted intercepts (π_{0sj}) and the predicted digital use at school slopes (π_{1sj}) and present the results in graphs (see the part on Figure 5.3 in Results).

5.5 Results

5.5.1 Disparities in Digital Learning Between Schools

Figure 5.1 shows the between-school gaps in digital use for schoolwork at home and Internet literacy in each country, with the size of the gap between high-SES schools (defined as schools in the top decile of *school SES mean*) versus low-SES schools (schools in the bottom decile of *school SES mean*) in the verticals in 42 countries. Overall, the effects of school SES on the two outcomes differ substantially across 42 countries of analysis. Poor countries tend to have higher levels of the between-school digital divide compared to rich countries. Taking the top graph as an example, the five countries with the greatest gap in digital use for schoolwork at home by school SES are Thailand, Chile, Panama, Russian Federation, and Trinidad and Tobago. In contrast, Slovenia, Portugal, Denmark, Germany, and Belgium have the smallest gap in digital use for schoolwork at home. However, it is also notable that the gaps also vary among countries with similar economic standing. This suggests the need to move beyond economic explanations, and to judge what other country-level factors may determine the digital divide between schools.

[Figure 5.1 about Here]

Table 5.2 shows results of three-level random-intercept modeling testing individual-level and school-level determinants of digital learning. Model 1 includes the effects of various individual-level characteristics on digital use for schoolwork at home. For each standard-deviation increase in digital use at school, digital use for schoolwork at home increases by .349 standard deviations (p<.01). Also, a one standard-deviation increase in family SES increases digital use for schoolwork at home by .178 standard deviations. These suggest that there is a strong association between the use of digital technology at school and digital use for schoolwork at home. In addition, family SES strongly predicts student digital learning at home.

[Table 5.2 about Here]

The main purpose of this table is to examine how digital learning opportunities vary between schools, and particularly between higher-SES and lower-SES schools. As shown in Model 1, a one standard-deviation increase in school average SES increases individual student's use of digital technology for schoolwork by .228, net of individual-level factors. Note that the effect of school SES is not only statistically significant (p<.01) but large in magnitude. In Model 2, when including other school-level control variables, the estimated average effect of school SES decreases only slightly by 20 percent and remains statistically significant (β=.183, p<.01).

Models 3 and 4 present the effects of individual-level and school-level variables on Internet literacy. As shown in these models, students who use digital technology more frequently at school, and also those from higher SES families, are associated with higher Internet literacy. When taking both individual-level and school-level control variables into account, the positive effect of school SES on Internet literacy remains large and is statistically significant. For each standard-deviation increase in school SES, Internet literacy increases by .090 standard deviations (p<.01).

Most of the individual-level controls perform as expected. Students attending a higher school grade than average are associated with higher levels of digital use for schoolwork at home and higher Internet literacy, as are those from immigrant versus non-immigrant families. This finding suggests that when controlling for other socio-demographic characteristics, immigrant students are not disadvantaged in the use of digital technology compared to their non-immigrant peers. Interestingly, speaking a foreign language at home has a positive effect on digital use for schoolwork at home, but a negative effect on Internet literacy. Compared to two-parent families, living in single-parent families reduces digital use for schoolwork at home but increases levels of Internet literacy. Finally, male students are less likely to use digital technology for schoolwork at home, but their level of Internet literacy is higher than female students. These findings, similar to the results of Table 4.2 in Chapter 4, are consistent with previous literature that suggests a greater tendency for male students than female students to use computers for non-educational activities, such as gaming (Imhof et al. 2007), and that girls tend to report lower self-assessment of online skills than boys (Hargittai and Shafer 2006).

Regarding the effects of school-level controls (Model 2 and 4), students in rural schools and town schools are less likely to use digital technology for schoolwork at home and to have lower Internet literacy compared to students attending urban schools. After controlling for other school-level factors, class size does not have a negative impact on student digital learning. Also, teacher shortage and school resource quality do not have independent effects on the digital learning opportunities of students. Taken together, I conclude that students in higher-SES schools have greater digital learning opportunities than those in lower-SES schools, and that this gap remains even when I control for students' backgrounds, their availability of digital use at school, and several school-level characteristics (e.g., proximity to cities, class size, and the

school's basic educational resources).

5.5.2 Sources of Cross-National Variation

Table 5.3 shows results of three-level random-slope models that examine how the effect of school SES varies systematically across countries. In a model that does not contain any country-level variable (but includes all individual- and school-level variables listed in Table 5.2), the country-level variance in school SES is .028 when predicting digital use for schoolwork at home, and .031 when predicting Internet literacy. This suggests that, among 95% of the countries included in my analysis, the impact of school SES on digital use for schoolwork at home ranges between −.157 and .501 standard deviations, and the coefficients of school SES predicting Internet literacy range from −.244 to .448. This demonstrates again that the size of school average SES effects vary substantially across countries.

[Table 5.3 about Here]

To evaluate key determinants of the level of digital learning inequality between schools with varying socioeconomic compositions, I include GNI per capita, the Gini index, secondary educational expenditures as a percentage of GDP per capita, and R&D as a percentage of GDP in each model (Model 1 to Model 4 for digital use for schoolwork at home; Model 5 to Model 8 for Internet literacy). All analyses include the same individual-level and school-level control variables shown in Table 5.2. The top half of the table shows the effects of country-level measures on the intercept, and the bottom half of the table examines the effects of country-level variables on the slope of school SES (or, in other words, the level of digital learning inequality between high-SES schools *versus* low-SES schools).

Beginning with digital use for schoolwork at home, the average effect of school SES is

.172. This suggests that one standard deviation increase in school SES increases the use of digital technology for schoolwork at home by .172 standard deviations, holding individual- and school-level variables constant. GNI per capita decreases students' digital use for schoolwork at home (b=−.119, p<.05) and reduces the size of the school SES effect (see Model 1: b=−.074, p<.01). Countries with higher levels of income inequality, measured by the Gini index, are associated with higher levels of between-school digital learning inequality by school SES (Model 2). Moreover, increases in secondary educational expenditures (Model 3) and R&D (Model 4) lead to reductions in the level of the digital divide between lower- and higher-SES schools.

Moving to Internet literacy (Model 5 to Model 8), I find similar results for country-level effects. GNI per capita reduces both students' Internet literacy (b=−.112, p<.10) and the Internet literacy gap by school SES (b=−.136, p<.01). As the level of a nation's income inequality increases, the Internet literacy gap between lower-SES and higher-SES schools widens. Both secondary educational expenditures and R&D significantly reduce the effect of school SES on Internet literacy.

In Table 5.3, I also test if the effects of the Gini index, educational expenditures, and R&D spending hold after adding GNI per capita as a control variable (full results available upon request). Beginning with digital use for schoolwork at home, the effects of the Gini index (Model 2) and secondary educational expenditures (Model 3) on the slope of school SES remain statistically significant (p<.05) when including GNI per capita in the models, and the size of these effects remain large (b=.241 for the Gini index; b=−.222 for secondary educational expenditures). Turning to Internet literacy, by contrast, the inclusion of GNI per capita in models significantly reduces the size of the effects of the three country-level variables on school SES slope (Model 6 to Model 8, respectively). Taken together, supplementary analyses suggest that

both income inequality and educational expenditures are strong predictors for the effect of school SES on digital use for schoolwork at home. On the other hand, economic development is a powerful predictor of the Internet literacy divide by school SES.

5.5.3 School Investment in Digital Technology

Does the use of digital technology at school promote digital learning? And how do the relationships differ between schools and cross-nationally? Figure 5.2 presents the gap in digital use at school across 42 countries, with the vertical lines representing the size of the gap between high-SES schools and low-SES schools. Among most countries, and particularly in countries such as Latvia, Greece, Hungary, and Lithuania listed on the right-hand side of the figure, students of low-SES schools tend to use digital technology in classrooms more often than those attending high-SES schools. The gap is almost nonexistent for countries such as Denmark, New Zealand, Iceland, Korea, and Serbia. There are only a few countries where students of high-SES schools have higher digital use at school than those of low-SES schools; these countries include Panama, Uruguay, Australia, Canada, and Sweden (see the left-hand side of the figure). In sum, this figure clearly reveals a great deal of country-level variation in the magnitude of the between-school gap in digital use at school, with no systematic link to national income apparent (supplementary findings available upon request).

[Figure 5.2 about Here]

Table 5.4 presents multilevel analyses of the effect of students' digital use at school on their digital learning outcomes (i.e., digital use for schoolwork at home and Internet literacy). Based on Hypothesis 5.3, I focus on the cross-level interactions between digital use at school (individual-level), school SES (school-level), and GNI per capita (country-level). In other words,

I examine how the relationship between digital use at school and digital learning outcomes differs along the line of school socioeconomic composition and varies by national income level. When modeling, I first include school SES (Model 1 for digital use for schoolwork at home; Model 3 for Internet literacy). I then add GNI per capita and its interaction with the school SES variable in Models 2 and 4.

[Table 5.4 about Here]

There are three notable interactions. First, the top half of the table suggests that school SES positively predicts both digital use for schoolwork at home and Internet literacy, but the size of the positive effect reduces as GNI per capita increases (Model 2: $b=-.070$; Model 4: $b=-.143$). Second—moving to the bottom half of the table—Model 2 further shows that the association between digital use at school and digital use for schoolwork at home becomes weaker as school SES increases ($b=-.048$). Third, Model 4 suggests that the effect of school SES on the slope of digital use at school depends upon GNI per capita ($b=.035$).

To better explain the patterns of these notable interactions, I plot the predicted intercepts and the predicted slopes of digital use at school by levels of school average SES and national income in Figure 5.3, which are calculated from Model 4 in Table 5.4. The left graph presents the effect of school SES on the intercept (i.e., predicted Internet literacy); the right graph presents how school SES affects the relationship between school digital use and Internet literacy. The figure presents six ideal types of countries, with GNI per capita of $5,000, $10,000, $20,000, $30,000, $40,000, and $50,000 in U.S. dollars.

[Figure 5.3 about Here]

When looking at the left-hand graph, the slopes of school SES among lower income

countries are steeper than the slopes among countries with higher GNI per capita. This suggests that poor countries have higher levels of the between-school divide in Internet literacy. When comparing students from high SES schools, the level of Internet literacy is higher in poor countries than rich countries—this notable result can also be found in Figure 5.1. This may indicate that in poor countries schools with a greater majority of high SES students tend to put a great emphasis on the use of the Internet for learning purposes. In contrast, GNI per capita increases the level of Internet literacy among students in lower-SES schools, which suggests that increasing economic development promotes the digital learning opportunities among students attending schools with a greater proportion of socioeconomically disadvantaged pupils.

Moving to the right-hand graph, the effect of school SES on the slope of school digital use is negative among countries with lower levels of national income (e.g., see the two regression lines representing countries with a GNI per capita of $5,000 and $10,000, respectively). Examples of these countries from my sample, in Appendix 5.2, include Thailand ($4,160), Serbia ($6,040), and Chile ($10,030). The negative effect disappears as a nation's GNI per capita reaches $20,000. The effect becomes positive among countries with higher levels of GNI per capita, such as Canada ($43,060), Finland ($48,590), and Sweden ($51,900). Overall, these findings support Hypothesis 5.3, which proposes that the use of digital technology in school significantly reduces the advantage of attending a higher-SES school over attending a lower-SES school, among students in poor countries. For students in rich countries, on the other hand, the potential benefits of digital use at school are greater for students attending a higher-SES or elite school than for those in a lower-SES or resource-poor school.

5.6 Discussion and Conclusion

Previous studies have found persistent disparities in digital learning at the school level (OECD

2011b; UNESCO 2015), which are mainly explained by discrepancies in school resources, teacher quality, and school availability of digital use (Natriello 2001; Warschauer 2000). After accounting for these factors, however, it is not clear whether the use of digital technology in the classroom would reduce or reproduce existing digital learning inequalities. Moreover, the national-level factors that contribute to the disparity across schools have received little attention. In this chapter, I find that the digital learning opportunities of students differ across schools and vary cross-nationally in the following ways:

First, after controlling for factors like school resources and the availability of digital access at school, students in socioeconomically advantaged schools are more likely to use a computer for schoolwork at home and have higher online literacy compared to students from socioeconomically unprivileged schools. And the effect of school SES is large in magnitude. I point out that not only do the socioeconomic backgrounds of students matter (Attewell 2001), but also that schools with wide variation in student socioeconomic profiles provide different digital learning experiences for individual students.

Second, there is substantial cross-national variation in the level of digital learning inequality between higher-SES and lower-SES schools. On one hand, both a country's overall income inequality and its expenditures on secondary education influence the between-school disparities in the use of digital technology for schoolwork. On the other hand, I find national income level, measured by GNI per capita, to be a powerful predictor of the Internet literacy gap between schools. Furthermore, increasing R&D investments is associated with decreasing the digital learning inequalities at the school level; this effect is moderate. Given these findings, I have extended previous literature on the global digital divide, which focus exclusively on economic factors based on adult samples (Robison and Crenshaw 2010). I argue that future

qualitative and quantitative researchers should explore specific policies or educational practices that are directly related to improving the digital learning opportunities of students in socioeconomically disadvantaged or resource-poor schools.

Third and most important, I ask whether the increasing use of digital technology in the classroom reduces the relative advantage of attending a higher-SES school in both rich and poor countries. While the use of digital technology at school positively predicts digital learning, I find that this relationship differs across schools and between countries, which also supports Hypothesis 5.3. Among poor countries, where school resources are more unevenly distributed and a great proportion of socio-economically underprivileged individuals have no access to a computer or the Internet at home, the benefits of digital use at a school are greater for students attending low-SES schools than those in high-SES schools. Among affluent countries, on the other hand, students attending high-SES schools receive more benefit from school use of digital technology compared to those in low-SES schools. This implies that in more affluent countries the increasing use of digital technology in the classroom does not reduce, but increases, the advantage of attending a socioeconomically advantaged school. The findings are in line with previous scholarship that suggests a persistent or "maximally maintained" educational inequality in more developed countries, despite their high levels of educational expansion and human capital investment (Hannum and Buchmann 2005; Raftery and Hout 1993).

Table 5.1: Descriptive Statistics and Variable Descriptions in the Analysis

Variable	Mean	SD	Description / Coding
Individual-level variables:			
Digital use for schoolwork at home	0.00	1.00	Standardized variable based on five activities at home (Cronbach's a = .79): browsing the Internet for schoolwork (e.g. prepare an essay), using e-mail to communicate with other students about schoolwork, using e-mail to communicate with teachers and submission of schoolwork, using material from your school's website, (e.g. course materials), and checking the school's website for announcements (e.g. absence of teachers). Response categories from lower to higher values are: "never or hardly ever", "once or twice a month", "once or twice a week", and "every day or almost every day".
Internet literacy	0.00	1.00	Standardized variable based on five online reading activities (Cronbach's a = .78): reading online news, using an online dictionary or encyclopedia (e.g., Wikipedia), searching online information to learn about a particular topic, taking part in online group discussions or forums, and searching for practical information online (e.g., schedules, events, tips, recipes). Response categories from lower to higher values are: "I don't know what it is", "never or almost never", "several times a month", "several times a week", and "several times a day".
Digital use at school	0.01	1.01	Standardized variables based on nine activites at school (Cronbach's a = .85): chatting online, using e-mail, browsing the Internet for schoolwork, using material from the school's website, posting your work on the school's website, playing simulations, practicing and drilling (e.g., foreign language learning), doing individual homework on a school computer, and using school computers for group work and communication with other students. Response categories from lower to higher values are: "never or hardly ever", "once or twice a month", "once or twice a week", and "every day or almost every day".

(continued)

Table 5.1: (*continued*)

Variable	Mean	SD	Description / Coding
Family SES	0.00	1.00	Standardized and PISA-created index of economic, social, and cultural status (OECD 2012), including: parental occupation status expressed as the index of ISEI, parental education in years, and an index of household possessions (e.g., a room for the child, possessions of classical literature, a desk for the child to study at home, the number of books at home).
Male	0.49	0.50	1 = male, 0 = female
School grade	-0.16	0.58	Measure of student progress in school. 0 represents students attending school at the same grade as most of other students of the same age within their country. A negative integer (coded -1, -2, etc.) or a positive integer (coded 1, 2, etc.) indicates students are at a grade below or above their expected grade level.
First generation immigrant	0.05	0.22	1 = yes, 0 = no. Reference group = non-immigrant.
Second generation immigrant	0.07	0.25	1 = yes, 0 = no. Reference group = non-immigrant.
Foreign language use at home	0.12	0.32	1 = yes, 0 = no
Single-parent family	0.16	0.36	1 = yes, 0 = no. Reference group = two-parent family.
Other family	0.03	0.16	1 = yes, 0 = no. Reference group = two-parent family.
School-level variables:			
School SES	-0.09	0.65	Mean of family SES.
Rural	0.11	0.31	1 = yes, 0 = no. Reference group = City.
Town	0.54	0.50	1 = yes, 0 = no. Reference group = City.
Class size	23.80	6.83	Mean of a student reported variable representing the number of students attending a language class.
Teacher shortage	0.00	0.98	Standardized variable based on the lack of teachers in four fields (Cronbach's a = .87): science teachers, mathematics teachers, qualified language teachers, and qualified teachers of other subjects. Response categories from lower to higher values are: "not at all", "very little", "to some extent", and "a lot".
School resource quality	-0.03	0.99	Standardized variable based on the shortage or inadequacy of seven indicators (Cronbach's a = .87): science laboratory equipment, instructional materials (e.g. textbooks), computers for instruction, Internet connectivity, computer software for instruction, library materials, and audio-visual resources. Response categories from lower to higher values are: "a lot", "to some extent", "very little", and "not at all".

(continued)

Table 5.1: (*continued*)

Variable	Mean	SD	Description / Coding
Country-level variables (all natural log transformed)			
GNI per capita	3.10	0.80	Gross National Income per capita in thousands of 2009 purchasing power parity (PPP) dollars.
Gini index	3.50	0.24	The distribution 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.
Secondary educational expenditures as % of GDP per capita	3.09	0.36	Current public spending on secondary education divided by the total number of students in this level. Public expenditure (current and capital) includes government spending on educational institutions (both public and private), education administration, and subsidies for private entities (students/households and other privates entities).
R&D as % of GDP	0.14	0.93	Research and Development including both public and private expenditures that cover basic research, applied research, and experimental development.

Data Source: All individual-level variables are from the Programme for International Student Assessment (PISA) 2009; GNI per capita and R&D are compiled from the World Bank's World Development Indicators (2015c); Gini index is from UNU-WIDER's (2008) World Income Inequality Database; secondary educational expenditures are from the World Bank's Education Statistics (2015a).
Note: To preserve cases, multiple imputations (*m* =1) for missing cases are used for individual-level control variables.

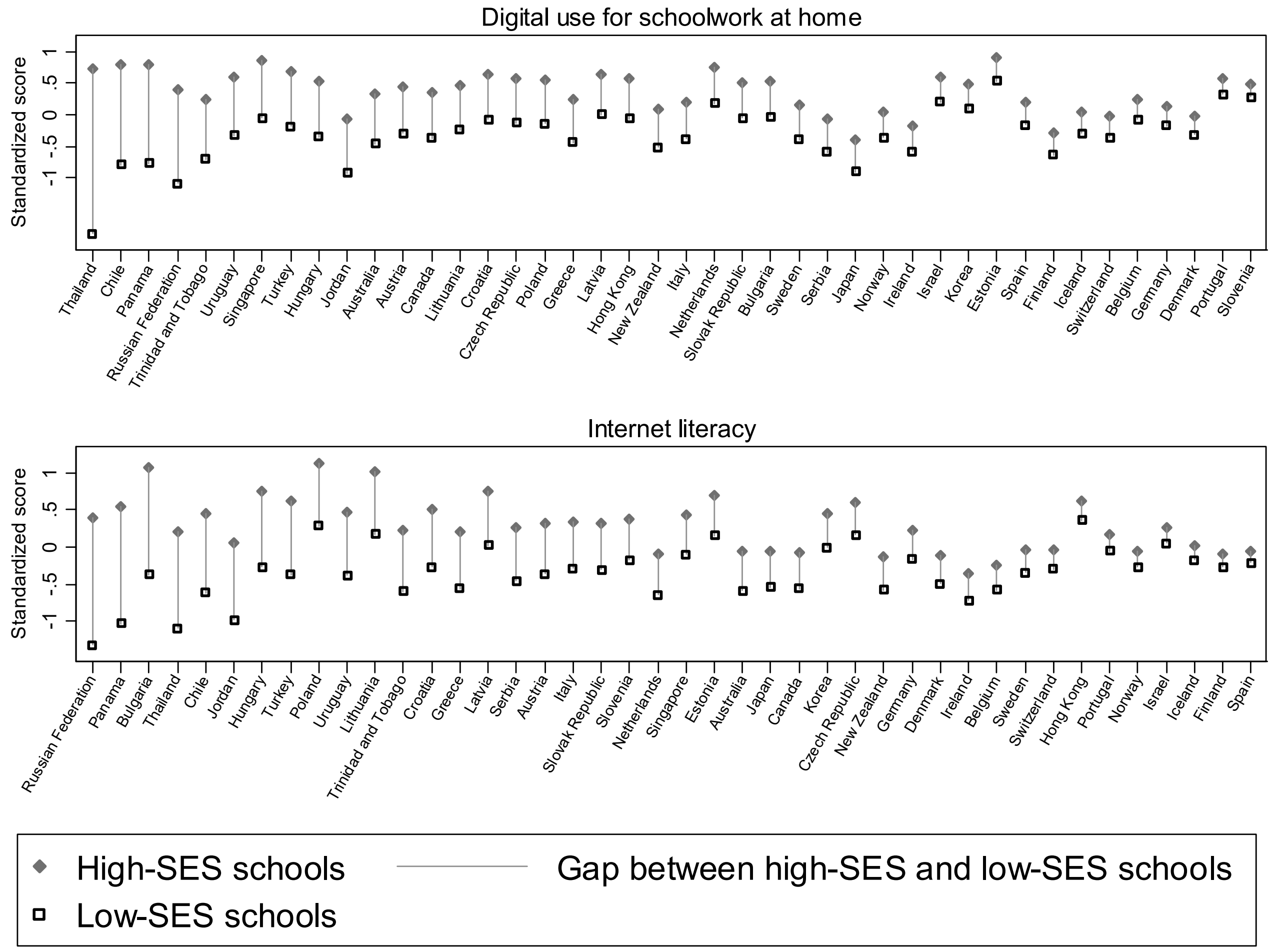


Figure 5.1: The Gaps in Digital Use for Schoolwork at Home and Internet Literacy by School SES

Note: The gaps in 1) digital use for schoolwork at home and 2) Internet literacy are calculated based on two-level HLM for each of the 42 countries, where students are considered as Level 1 and schools are considered Level 2. Each model includes Level 1 control variables (gender, school grade, immigration status, foreign language use at home, and family structure). The line attached to each country represents the size of the gap between the average of high-SES schools (i.e., the top decile of schools' average SES) and the average of low-SES schools (i.e., the bottom decile of schools' average SES). Countries are ranked in descending order of the size of the gap between high-SES and low-SES schools.

Table 5.2: Multilevel Analyses of the Between-School Digital Divide: Individual- and School-Level Variables

	Digital use for schoolwork at home[a]		Internet literacy[b]	
	Model 1	Model 2	Model 3	Model 4
Intercept	.029 (.053)	.062 (.052)	-.033 (.051)	.009 (.049)
Digital use at school	.349 (.002)**	.350 (.002)**	.169 (.002)**	.170 (.002)**
Family SES	.178 (.002)**	.178 (.002)**	.221 (.002)**	.221 (.002)**
Male	-.038 (.003)**	-.037 (.003)**	.109 (.004)**	.109 (.004)**
School grade	.008 (.004)*	.006 (.004)+	.106 (.004)**	.104 (.004)**
First generation immigrant	.143 (.009)**	.137 (.009)**	.205 (.009)**	.197 (.009)**
Second generation immigrant	.148 (.008)**	.141 (.008)**	.205 (.008)**	.195 (.008)**
Foreign language use at home	.030 (.006)**	.030 (.006)**	-.020 (.007)**	-.020 (.007)**
Single-parent family	-.058 (.004)**	-.060 (.004)**	.016 (.005)**	.015 (.005)**
Other family	-.033 (.011)**	-.032 (.011)**	-.089 (.011)**	-.088 (.011)**
School SES	.228 (.006)**	.183 (.007)**	.133 (.006)**	.090 (.006)**
Rural		-.177 (.012)**		-.157 (.011)**
Town		-.044 (.007)**		-.065 (.006)**
Class size		.006 (.001)**		.006 (.001)**
Teacher shortage		-.003 (.004)		-.005 (.003)
School resource quality		.005 (.003)		-.002 (.003)
Variance components				
Between-country intercept variance	.118	.111	.108	.102
Between-school intercept variance	.063	.060	.041	.039
Individual-level variance	.690	.690	.790	.790
Log-likelihood	-346,491	-346,311	-363,327	-363,137
$N_{\text{Individual-level}}$	275,810	275,810	275,810	275,810

Note: Number of countries = 42. Number of schools = 10,235. Standard errors are in parentheses. All coefficients are adjusted by multiple imputations for missing cases in the control variables ($m = 1$). [a] For an intercept-only model: between-country intercept variance is .112; between-school intercept variance is .110; individual-level variance is .805. The intraclass correlation (ICC) is .109 at the country-level; .107 at the school-level. [b] For an intercept-only model: between-country intercept variance is .086; between-school intercept variance is .073; individual-level variance is .853. ICC is .085 at the country-level; .072 at the school-level.

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

Table 5.3: Multilevel Analyses of the Between-School Digital Divide: Country-Level Variables

	Digital use for schoolwork at home				Internet literacy			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Effects on the Intercept [a]								
Intercept	.077 (.047)	.078 (.048)	.078 (.049)	.078 (.048)	.019 (.046)	.019 (.048)	.019 (.048)	.019 (.047)
GNI per capita	-.119 (.060)*				-.112 (.058)+			
Gini index		.322 (.205)				.196 (.203)		
Secondary educational expenditures as % of GDP per capita			-.050 (.137)				.002 (.133)	
R&D as % of GDP				-.086 (.052)+				-.057 (.051)
Effects on the School SES Slope [a]								
Intercept	.172 (.025)**	.172 (.025)**	.171 (.023)**	.172 (.025)**	.101 (.023)**	.102 (.027)**	.101 (.027)**	.101 (.026)**
GNI per capita	-.074 (.032)*				-.136 (.029)**			
Gini index		.307 (.104)**†				.238 (.113)*		
Secondary educational expenditures as % of GDP per capita			-.242 (.063)**†				-.142 (.074)+	
R&D as % of GDP				-.062 (.027)*				-.079 (.028)**
Variance components								
Between-country intercept variance	.092	.095	.100	.094	.088	.094	.096	.093
Between-country school SES variance	.024	.023	.020	.025	.020	.028	.028	.026
Between-school intercept variance	.051	.051	.051	.051	.033	.033	.033	.033
Individual-level variance	.690	.690	.690	.690	.790	.790	.790	.790
Log-likelihood	-345,825	-345,825	-345,824	-345,826	-362,694	-362,704	-362,704	-362,702
$N_{\text{Individual-level}}$	275,810	275,810	275,810	275,810	275,810	275,810	275,810	275,810

Note: Number of countries = 42. Number of schools = 10,235. Standard errors are in parentheses. All coefficients are adjusted by multiple imputations for missing cases in the control variables ($m = 1$). [a]All models include individual-level control variables (digital use at school, family SES, gender, school grade, immigration status, foreign language use at home, and family structure) and school-level control variables (rural/town, class size, teacher shortage, and school resource quality). All continuous variables at the individual-, school-, and country-levels are grand mean centered. All country-level variables are natural log transformed. † indicates the effect remains statistically significant (p <.05) if adding GNI per capita as a control variable.

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

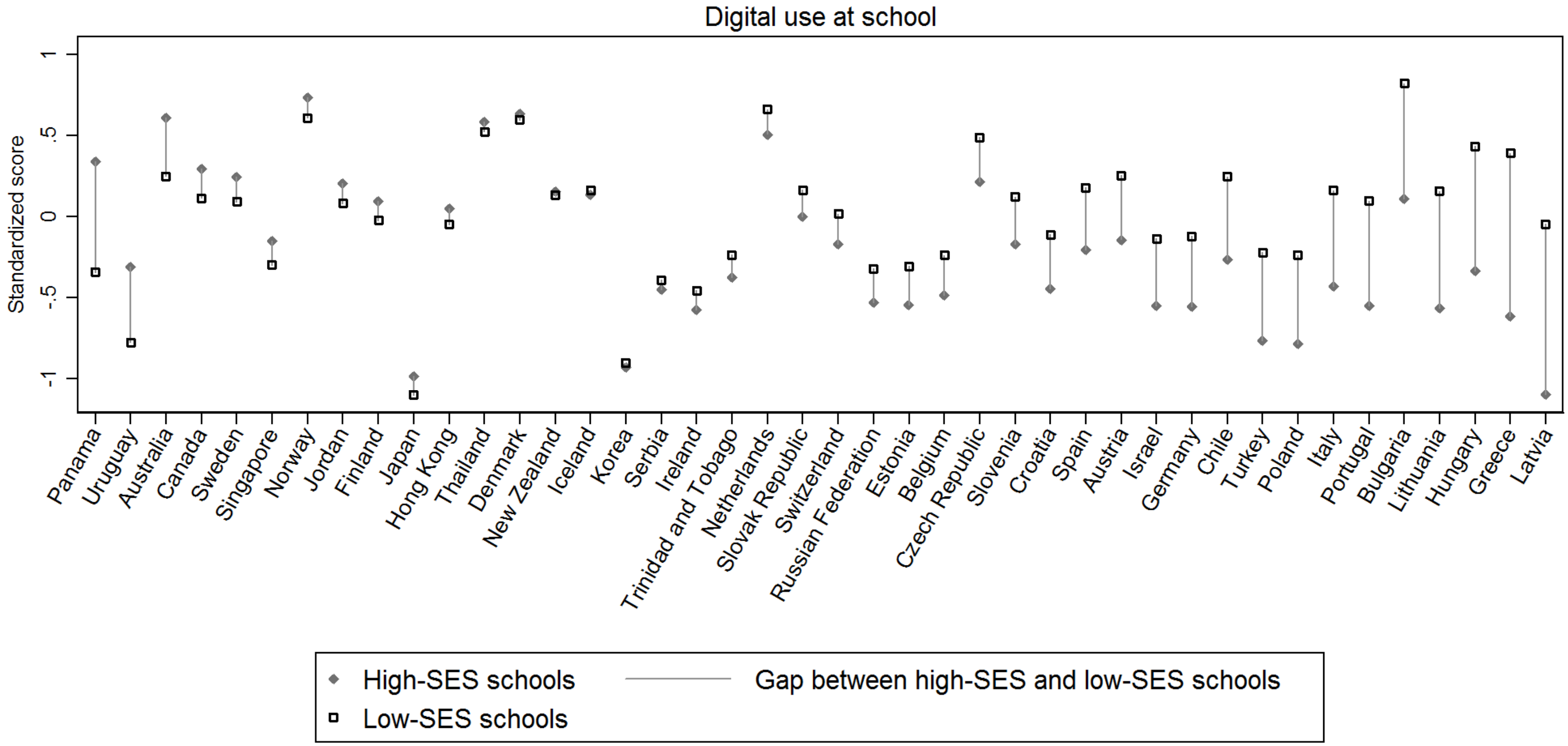


Figure 5.2: The Gaps in Digital Use at School by School SES

Note: The gaps in digital use at school are calculated based on two-level HLM for each of the 42 countries, where students are considered as Level 1 and schools are considered Level 2. Each model includes Level 1 control variables (gender, school grade, immigration status, foreign language use at home, and family structure). The line attached to each country represents the size of the gap between the average of high-SES schools (i.e., the top decile of schools' average SES) and the average of low-SES schools (i.e., the bottom decile of schools' average SES). Countries are ranked in descending order of the size of the gap between high-SES and low-SES schools.

Table 5.4: Multilevel Analyses of the Effect of Digital Use at School on Digital Learning Outcomes: Differential Effects by School SES and GNI Per Capita

	Digital use for schoolwork at home		Internet literacy	
	Model 1	Model 2	Model 3	Model 4
Effects on the Intercept [a]				
Intercept	.044 (.049)	.045 (.047)	-.005 (.048)	-.004 (.046)
School SES	.167 (.027)**	.166 (.025)**	.096 (.028)**	.093 (.023)**
GNI per capita		-.125 (.059)*		-.116 (.058)*
School SES × GNI per capita		-.070 (.032)*		-.143 (.029)**
Effects on the Digital Use at School Slope [a]				
Intercept	.357 (.014)**	.356 (.014)**	.169 (.012)**	.169 (.011)**
School SES	-.048 (.010)**	-.048 (.010)**	.001 (.008)	.004 (.007)
GNI per capita		.028 (.017)		.015 (.014)
School SES × GNI per capita		.016 (.012)		.035 (.009)**
Variance components				
Between-country intercept variance	.101	.091	.096	.087
Between-country school SES variance	.028	.024	.032	.020
Between-country digital use at school variance	.008	.007	.005	.004
Between-country digital use at school/school SES variance	.003	.003	.002	.001
Between-school intercept variance	.048	.048	.030	.030
Between-school digital use at school variance	.017	.017	.010	.010
Individual-level variance	.670	.670	.779	.779
Log-likelihood	-343,877	-343,870	-361,935	-361,917
$N_{\text{Individual-level}}$	275,810	275,810	275,810	275,810

Note: Number of countries = 42. Number of schools = 10,235. Standard errors are in parentheses. All coefficients are adjusted by multiple imputations for missing cases in the control variables ($m = 1$). [a]All models include individual-level control variables (digital use at school, family SES, gender, school grade, immigration status, foreign language use at home, and family structure) and school-level control variables (rural/town, class size, teacher shortage, and school resource quality). All continuous variables at the individual-, school-, and country-levels are grand mean centered. All country-level variables are natural log transformed.

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

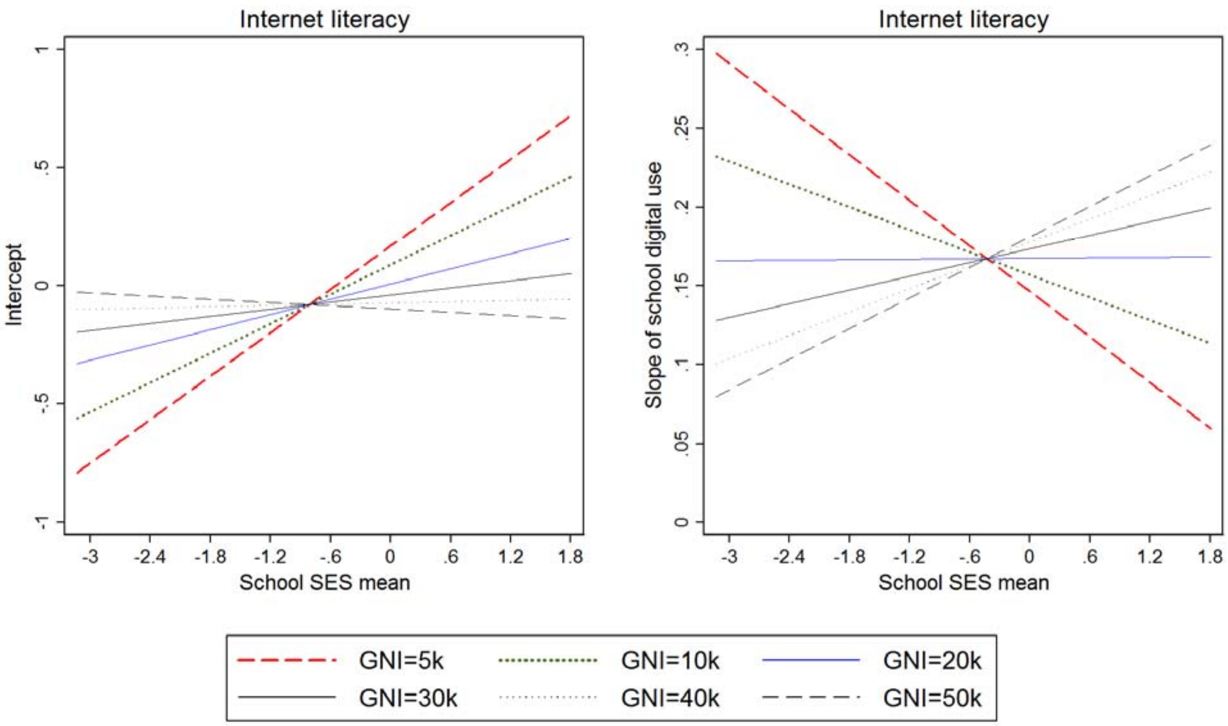


Figure 5.3: Predicted Intercept and Predicted Digital Use at School Slope by Schools' SES and Countries' GNI Per Capita

Note: Predicted intercept and predicted digital use at school slopes are calculated from Model 4 in Table 5.4. The plotted lines represent the association between school SES mean (*x*-axis) and intercept or the slope of digital use at school (*y*-axis). School SES mean is a standardized variable based on the mean of students' family SES in each school.

Appendix 5.1: Sample Size and Descriptive Statistics for Key Individual and School-Level Variables in 42 Countries

	Sample size		Digital use for schoolwork at home		Internet literacy		Digital use at school		School SES	
Country	Student	School	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Australia (AU)	14,251	350	.10	.87	-.13	.89	.44	.70	.30	.39
Austria (AT)	6,590	221	.07	.91	.01	.89	.13	.95	.08	.42
Belgium (BE)	8,501	252	-.04	.83	-.34	.83	-.32	.96	.19	.52
Bulgaria (BG)	4,507	138	.52	1.14	.42	1.20	.54	1.20	-.10	.56
Canada (CA)	23,207	916	.08	.94	-.19	.95	.25	.81	.45	.40
Chile (CL)	5,669	158	-.08	1.14	-.12	.99	.07	.96	-.51	.85
Croatia (HR)	4,994	153	.13	.94	.16	.99	-.19	1.04	-.17	.46
Czech (CZ)	6,064	228	.29	.92	.56	.91	.29	.90	.00	.39
Denmark (DK)	5,924	278	.23	.77	.09	.86	.75	.67	.12	.44
Estonia (EE)	4,727	166	.63	.73	.50	.89	-.39	.98	.13	.36
Finland (FI)	5,810	191	-.49	.78	-.10	.83	.10	.67	.41	.31
Germany (DE)	4,979	190	-.09	.80	.11	.87	-.26	.88	.19	.46
Greece (GR)	4,969	170	-.02	1.16	-.03	1.05	.03	1.23	-.03	.56
Hong Kong (HK)	4,837	150	.14	.79	.47	.86	.12	.91	-.83	.57
Hungary (HU)	4,605	161	.12	.91	.43	.98	.00	.98	-.26	.67
Iceland (IS)	3,646	104	-.05	.91	.18	.94	.08	.85	.52	.41
Ireland (IE)	3,937	123	-.58	.91	-.49	.88	-.40	.97	.02	.45
Israel (IL)	5,761	151	.28	1.03	.16	.97	-.25	1.16	-.01	.47
Italy (IT)	30,905	1,015	-.17	.93	.00	1.03	-.11	.93	-.12	.52
Japan (JP)	6,088	186	-.95	.85	-.41	.97	-1.05	.76	-.03	.37
Jordan (JO)	6,486	208	-.24	1.22	-.42	1.17	.26	1.11	-.51	.55
Korea (KR)	4,989	156	-.01	.81	.08	.88	-.91	.93	-.14	.44
Latvia (LV)	4,502	178	.27	.92	.43	.92	-.50	1.06	-.14	.46
Lithuania (LT)	4,528	188	.09	.91	.61	.99	-.17	1.01	-.13	.55
Netherlands (NL)	4,760	174	.64	.66	-.14	.85	.57	.69	.32	.42
New Zealand (NZ)	4,643	155	-.12	.90	-.22	.86	.13	.81	.06	.38
Norway (NO)	4,660	187	.16	.77	.15	.85	.75	.67	.46	.26
Panama (PA)	3,969	153	.11	1.20	-.22	1.15	.12	1.10	-.80	.88
Poland (PL)	4,917	180	.02	.91	.61	.97	-.36	.94	-.19	.57
Portugal (PT)	6,298	203	.41	.89	.12	.90	.05	1.08	-.34	.63
Russia (RU)	5,308	195	-.40	1.19	-.36	1.23	-.30	1.15	-.24	.44
Serbia (RS)	5,523	170	-.50	1.10	-.16	1.10	-.36	1.05	.09	.46
Singapore (SG)	5,283	170	.27	.98	.15	.98	-.09	.98	-.43	.37
Slovakia (SK)	4,555	179	.18	1.05	.06	1.00	.17	.92	-.12	.40
Slovenia (SI)	6,155	277	.40	.91	.19	.95	.04	1.14	-.08	.46
Spain (ES)	25,887	847	.01	.93	-.12	.90	.03	.94	-.27	.56
Sweden (SE)	4,567	176	-.07	.86	.01	.88	.23	.75	.34	.36
Switzerland (CH)	11,812	400	-.16	.86	-.07	.87	.02	.84	.00	.35
Thailand (TH)	6,225	224	-.72	1.41	-.41	1.07	.55	.93	-1.30	.95
Trinidad & Tobago (TT)	4,778	149	-.34	1.14	-.35	1.02	-.25	1.10	-.60	.49
Turkey (TR)	4,996	158	.20	1.10	.15	1.07	-.34	1.15	-1.22	.75
Uruguay (UY)	5,957	210	-.06	1.21	-.11	1.04	-.35	1.17	-.82	.80

Appendix 5.2: Country-Level Variables: 42 Countries

	GNI per capita	Gini index	Secondary educational expenditures as % of GDP per capita	R&D as % of GDP
Low-income countries				
Jordan (JO)	3.90	.39	14.79	.43
Thailand (TH)	4.16	.42	8.94	.25
Serbia (RS)	6.04	.39	14.39	.87
Bulgaria (BG)	6.64	.31	24.95	.51
Panama (PA)	7.69	.55	15.76	.14
Uruguay (UY)	8.77	.45	10.69	.42
Turkey (TR)	9.13	.45	10.95	.85
Russia (RU)	9.23	.45	23.00	1.25
Chile (CL)	10.03	.55	16.61	.35
Poland (PL)	12.40	.37	24.23	.67
Lithuania (LT)	12.52	.35	26.16	.83
Hungary (HU)	13.27	.26	22.83	1.14
Croatia (HR)	13.81	.29	25.20	.84
Latvia (LV)	13.86	.39	30.68	.45
Mean	9.39	.40	19.23	.64
Mid-income countries				
Estonia (EE)	14.47	.33	32.63	1.40
Trinidad & Tobago (TT)	16.19	.40	9.90	.06
Slovakia (SK)	17.00	.24	18.24	.47
Czech (CZ)	18.65	.25	24.33	1.30
Korea (KR)	21.09	.32	23.81	3.29
Portugal (PT)	22.84	.38	38.71	1.58
Slovenia (SI)	24.40	.24	24.78	1.82
Israel (IL)	27.18	.37	16.04	4.15
Greece (GR)	29.07	.34	21.55	.63
New Zealand (NZ)	29.41	.34	18.72	1.26
Mean	22.03	.32	22.87	1.60
High-income countries				
Hong Kong (HK)	32.35	.51	16.40	.77
Spain (ES)	32.77	.31	28.46	1.35
Singapore (SG)	37.08	.48	15.89	2.16
Japan (JP)	37.47	.32	22.39	3.36
Italy (IT)	37.69	.32	26.63	1.22
Iceland (IS)	42.21	.26	22.66	2.66
Canada (CA)	43.06	.32	23.00	1.92
Germany (DE)	43.81	.27	24.72	2.73
Australia (AU)	44.01	.29	18.57	2.40
Belgium (BE)	46.25	.28	37.90	1.97
Ireland (IE)	47.16	.32	30.05	1.63
Finland (FI)	48.59	.26	36.11	3.75
Austria (AT)	48.71	.25	30.62	2.61
Sweden (SE)	51.90	.23	33.03	3.42
Netherlands (NL)	53.52	.26	27.19	1.69
Denmark (DK)	59.84	.24	32.98	3.07
Switzerland (CH)	70.23	.31	28.62	2.73
Norway (NO)	87.84	.30	28.89	1.72
Mean	48.03	.31	26.89	2.29

Note: GNI per capita is in thousands of 2009 purchasing power parity dollars. The classification of income groups is based on the World Bank (2015b). Countries within groups are sorted by GNI per capita. All of the country-level data are from 2009.

Chapter 6:

Inequality of Digital Learning in Shanghai and Taiwan

In Chapters 4 and 5, I examined cross-national variation in digital learning inequality at the student- and school-level. Similar to previous research that uses large-scale, cross-national analysis, these chapters were only able to examine a limited number of country-level effects, while leaving others unexamined. In this chapter, I focus on 15-year-olds in Shanghai and Taiwan, and address how the patterns of digital learning inequality *within* and *between* schools differ between these two societies and certain other countries.

6.1 Problem Statement

The test results from the 2009 Programme for International Student Assessment (PISA) show that Shanghai outperforms all participating economies in every subject area, including reading, math, and science. Surprisingly, family socioeconomic status (SES) in Shanghai appears to have less impact on student academic performance than in most developed countries. The stunning achievements of Shanghai and other East Asian societies, such as Taiwan, Hong Kong, and Korea, have garnered considerable attention in educational research and media reports (Driskell 2014; OECD 2010b, 2011a; Ripley 2014; Sellar and Lingard 2013; Tan 2011, 2012). This reflects that leaders and government officers in the world are often "anxious to learn about educational practices in other countries, as they scan the latest international league tables of school performance (Broadfoot 2003:411)."

Despite the wealth of research on education and globalization that centers on the academic performance of students, there is a lack of information on how family background and school factors influence digital performance and Internet literacy for students in Shanghai and

other East Asian societies. This underexplored research agenda requires more attention, since scholars have long recognized the growing importance of information and communication technology (ICT) in the knowledge economy and the role of ICT in the learning society (European Commission 1994; Spring 2008), especially among the East Asian societies that have demonstrated astonishing economic development and technological progress (Drori 2006, 2010; Tsai and Kanomata 2012).

In this chapter, I examine the magnitude of digital learning inequality within and between two East Asian societies—Shanghai and Taiwan. By *digital learning inequality within and between schools*, I mean 1) the gap in Internet literacy *within schools* along socioeconomic lines, and 2) the relationship between student SES and Internet literacy that differs *between schools* with varying socioeconomic compositions. I chose Shanghai and Taiwan because they are two of the newly industrialized countries (NICs) that have similar cultural backgrounds and educational systems, but have substantial differences in their social institutional bases. This enables us to isolate the effects of that variable in comparing the systems.[19] On one hand, the schooling systems of both societies are highly stratified, to the extent that students are streamed into different programs and schools according to their prior academic performance (OECD 2011a:83–115). The parents in both places continue urge their children to attend the best available institution, despite an expansion in education that has led to a much broader range of upper secondary education options (OECD 2011a:83–115; Smith et al. 2016). In Shanghai, however, there is greater competition in the choice of schools than in Taiwan. As in most parts of China, affluent parents in Shanghai have more freedom to choose elite "key" public schools, with better teachers and more resources (OECD 2011a:95; Ye 2015; Zhou, Cai, and Wang

[19] Another reason to focus on Taiwan is because it was among the first Asian countries to rapidly expand secondary and post-secondary education (Smith et al. 2016).

2016), which give advantage to their children.[20] The 2009 PISA report also shows that the socioeconomic segregation of schools is stronger in Shanghai than in Taiwan and other highly industrialized countries (OECD 2011a:93). This suggests that disadvantaged students in Shanghai are more likely to attend resource-poor schools or schools with a majority of low-SES students.

On the other hand, both societies have implemented several nationally supported projects which support the development of "the information society" (James 2009), to keep up in "the race to lead the world in creating the next 'hot' technology (Drori 2010:80)." Both the Chinese and Taiwanese governments have considered the potential payoffs for public investment in computers and Internet connections in the classroom (Chen 2007; Mo et al. 2013). In 1998, for example, Shanghai's Second Curriculum Reform emphasized the incorporation of ICT in schools, with the aim of encouraging students to use ICT in their daily lives and in their learning (Shanghai Municipal Education Commission 2004; Tan 2012). Similar educational policies can be found in the 2001 educational reform reported by the Taiwanese Ministry of Education (Chen 2007; Ministry of Education 2006). Despite these efforts, however, empirical findings verify that a digital divide along socioeconomic lines persists in both societies (Drori 2007; Lin 2012; Pan, Tseng, and Lin 2009). Notably, the magnitude of the digital divide is strikingly different in the two societies: According to the results of PISA 2009 (OECD 2011b:149), in Shanghai only about 51 percent of low-SES students reported having Internet access at home, compared to 99 percent of high-SES students. In contrast, the gap in Internet access at home is much smaller in Taiwan

[20] "Key schools," which are selected by government authorities, are targeted schools that receive additional resources and have better teachers. To eliminate educational inequalities generated by key schools, Shanghai introduced neighborhood attendance at both primary and secondary schools since 1994, which required students to attend schools close to their residence. However, although most national key schools no longer exist, there are still a lot of key schools at the provincial and municipal levels. Because of the social pressure, Shanghai students can choose public schools in other neighborhoods by paying a sponsorship fee (OECD 2011a:95).

(90.8 % for low-SES students *versus* 100.0% for high-SES students).[21]

In this chapter, I address two research questions: Firstly, what are the key determinants of digital learning inequality? Secondly, how does the level of digital learning inequality vary between schools in Shanghai and Taiwan? In Shanghai, because there is greater competition among students, more school-choice opportunities for parents, and greater school segregation by the socioeconomic background of students (OECD 2011a; Zhou et al. 2016), I propose the following research hypothesis:

> *Hypothesis 6.1: the effect of family SES on Internet literacy is greater in Shanghai than in Taiwan. Moreover, the effect of school SES on the Internet literacy gap within schools is larger in Shanghai than Taiwan.*

More broadly, the third research question addresses how the patterns of digital learning inequality in Shanghai and Taiwan differ from seven other economically advanced or newly industrialized countries, including Hong Kong, Singapore, Korea, Japan, the United States, Canada, and Finland. Although I add only these seven countries that vary greatly by their institutional contexts, they are sufficient to depict how the digital learning inequalities in Shanghai and Taiwan vary from countries with similar economic standing or cultural background. For instance, students in other Chinese-based societies like Hong Kong and Singapore often experience greater competition in educational performance, and their educational systems tend to be highly stratified (OECD 2011a; Zhou et al. 2016)—like those in Shanghai and Taiwan. This is in stark contrast to students in Finland (Chmielewski 2014). I

[21] Among other highly industrialized Asian societies, the rate to Internet access at home is 87% for low-SES students and nearly 100% for high-SES students in Singapore, 95% for low-SES students and nearly 100% for high-SES students in Hong Kong, 92% for low-SES students and nearly 100% for high-SES students in Korea, and 55% for low-SES students and 96% for high-SES students in Japan.

define social segregation in schools as the inequality that results from the differences between schools with different socioeconomic profiles. Based on the comparison across nine societies, I focus on how that segregation affects the patterns of digital learning inequality *within* schools and *between* them. I propose the following hypothesis:

> *Hypothesis 6.2: as in Shanghai and Taiwan, societies with greater competition among students and higher levels of school segregation by SES have greater digital learning inequality within- and between-schools.*

Before the end of this chapter, I also explore whether income inequality affects the inequality of digital learning within schools and between them. Shanghai, like Hong Kong, has alarmingly high income inequality, with its Gini index nearing .49 in 2008 (Government of the Hong Kong SAR 2012; Shanghai Municipal People's Government 2013). While Taiwan has less income inequality, it has been labeled as a country with "above-average performance, and below average equity" (OECD 2014:194). Inspired by the global digital divide literature (Fuchs 2008; Martin and Robinson 2007; Ono and Zavodny 2007) and educational scholarship (Chiu and Khoo 2005; Chudgar and Luschei 2009; Wilkinson and Pickett 2009), I form a general hypothesis that the digital learning inequality in educational settings reflects broader inequalities based in the economy (*Hypothesis 6.3*). To do this, I run multilevel modeling that includes 67 countries. The main objective of this part is to give us a broad understanding of the patterns of the digital learning inequality in Shanghai and Taiwan, and their differences from the rest of the world.

6.2 Data

The data for this chapter was taken from the 2009 Programme for International Student Assessment (PISA) sample of 5,115 students across 152 schools in Shanghai, and 5,831 students

across 158 schools in Taiwan. The samples were considered to be representative of the 15-year-olds in various school types for both Shanghai and Taiwan. Students for whom either dependent variables or key independent variables were missing were discarded from the samples, leading to final sample sizes of 5,109 students across 151 schools in Shanghai, and 5,657 students across 154 schools in Taiwan.

A notable feature of PISA 2009 is the participation of several Chinese societies. The others are: Hong Kong, Macao, and Singapore, with each operating under different socio-political regimes. The use of standardized measurements in PISA allows me to compare students' digital performance across these Chinese societies, as well as other countries.

6.3 Measures

6.3.1 Dependent Variable

I use *Internet literacy* to represent the inequalities of digital learning both at the individual and school levels. It is a composite scale measuring how often students engage in the following five online reading activities (α=.79 for the Shanghai sample, .78 for the Taiwan sample): reading online news, using an online dictionary or encyclopedia (e.g., Wikipedia), searching online information to learn about a particular topic, taking part in online group discussions or forums, and searching for practical information online (e.g., schedules, events, tips, recipes).[22] Each component represents a particular aspect of online reading habits and the associated skills. A combination of these items indicates how familiar students are with reading text on the screen, sharing information and exchanging ideas, and interacting with others in a digital context. To ease interpretation of the results, both dependent variables are standardized with a mean of 0 and

[22] In the questionnaire, there were seven online reading activities. I exclude two of these activities—reading emails and chatting online—as they are not directly related to searching for information or acquiring knowledge.

a standard deviation of 1.

6.3.2 Student-Level Independent Variables

The key independent variable, *family SES*, is based on the PISA-created Index of Economic, Social, and Cultural Status (OECD 2012), which is the most commonly used measure of SES in studies using PISA data. The variable is a combination of three components: parental occupation status expressed as the index of the international socio-economic index of occupational status (ISEI) (Ganzeboom et al. 1992), parental education in years, and an index of household possessions, such as a room for the child, owning classical literature, a desk for the child to study at home, and the number of books at home. To ease interpretation of the results, the variable is standardized to have a mean of 0 and a standard deviation of 1.

In addition, I include four individual-level control variables.[23] *Gender* controls for the potential digital gap between male and female students (male=1). Because PISA samples 15-year-old students regardless of the grade they attend, I control for *school grade*. Students attending school at the same grade as most other students of the same age within their country are coded as 0. A negative integer (-1, -2, etc.) or a positive integer (1, 2, etc.) indicates the number of years students are either below or above their expected grade level. To control for differences in language used by immigrant students I include a dummy variable—*foreign language use at home*—with *use the same language at home as in school* as the reference category. I include this control because students who are not native speakers of the language used at school can often be academically disadvantaged compared to native-speaking students. To control for family structure, I include two dummy variables—*single-parent family* and *other*

[23] Unlike Chapter 4 and Chapter 5, I do not include immigration status as a control variable, because in both societies there were less than one percent of students who identified themselves as first- or second- generation immigrants.

family—with *two-parent family* as the reference category.

6.3.3 School-Level Independent Variables

The key independent variable, *school SES mean*, is an average of the student-reported family SES for each school, used to address the impact of the socioeconomic composition of the schools. I use this variable to examine the degree of digital learning inequality at the school-level (i.e., the effect of *school SES mean* on the two dependent variables).

There are several other school-level control variables used in the analyses. To control the amount of time and attention that teachers give to individual students, I control for *class size*, which is the average class size of the language of instruction calculated from students' self-reports (OECD 2010a:82). In the questionnaire, students were asked, "on average, about how many students attend your <test language> class?" To account for the effect of teacher attributes, I include *teacher shortage*, a PISA-created index indicating the lack of teachers in four fields (α=.95 for both Shanghai and Taiwan): science teachers, mathematics teachers, qualified language teachers, and qualified teachers of other subjects. Original response categories from lower to higher values are: "not at all", "very little, "to some extent", "and "a lot". To control for a school's overall educational resource quality, I use another PISA-created index, *school resource quality*, which measures the shortage or inadequacy of seven items (α=.94 for both Shanghai and Taiwan): science laboratory equipment, instructional material (e.g., textbooks), computers for instruction, Internet connectivity, computer software for instruction, library materials, and audio-visual resources. I also control for the difference between public and private schools (public=1).

I use several dummy variables to account for the effect of school type, with *other high school* as the reference category. *Middle school* refers to 15-year-olds who were still in lower

secondary education during the time of PISA survey. There are about three out of ten 15-year-olds (34% of students in Shanghai, and 26% of students in Taiwan) who attended lower secondary schools. For the Shanghai sample, in addition, I include two unique variables—*key high school* and *experimental model high school*. For the Taiwanese sample, I include one unique variable, *urban public high school*. In Taiwan, public high schools located in urban areas are often perceived as "good schools," while there is still substantial variation in student academic performance and teacher quality between them.

Lastly, to control for the difference between rural schools and schools in urban areas in Taiwan, I include three dummy variables—*small town*, *town*, and *large city*—with *city* as the reference category. Table 6.1 presents descriptive statistics and coding for all variables used in the analyses.

[Table 6.1 about Here]

6.4 Analytical Strategy and Statistical Methods

The analyses in this chapter proceed in three stages. The first stage focuses on individual-level and school-level determinants of digital learning. I use two-level random-slope modeling for *Internet literacy* and estimate the models separately in Shanghai and Taiwan. Each model includes several individual-level variables and one school-level variable. At the individual-level, the effect of family SES is allowed to vary randomly across schools. In the second stage, I use the same models separately for all nine countries and societies (i.e., Shanghai, Taiwan, Hong Kong, Singapore, Korea, Japan, the United States, Canada, and Finland), and use graphs to compare the impact of school SES on Internet literacy across the nine societies (results are presented in Figure 6.1).

The third and final stage broadly examines how the effect of *family SES* at the individual-

level differs between schools and varies across 67 countries. I use three-level random-slope models to formally account for school-level and country-level effects. The general form of the models can be written as,

$$Y_{isj} = \pi_{0sj} + \pi_{1sj}(Family\ SES)_{isj} + \sum_2^k \pi_{ksj} a_{isj} + e_{isj} \quad (1)$$

$$\pi_{0sj} = \beta_{00j} + \beta_{01j}(School\ SES)_{sj} + \sum_2^k \beta_{0kj} X_{sj} + r_{0sj} \quad (2)$$

$$\pi_{1sj} = \beta_{10j} + \beta_{11j}(School\ SES)_{sj} + \sum_2^k \beta_{1kj} X_{sj} + r_{1sj} \quad (3)$$

$$\beta_{00j} = \gamma_{000} + \gamma_{001}(Gini\ index)_j + \mu_{00j} \quad (4)$$

$$\beta_{01j} = \gamma_{010} + \gamma_{011}(Gini\ index)_j + \mu_{01j} \quad (5)$$

$$\beta_{10j} = \gamma_{100} + \gamma_{101}(Gini\ index)_j + \mu_{10j} \quad (6)$$

$$\beta_{11j} = \gamma_{110} + \gamma_{111}(Gini\ index)_j + \mu_{11j} \quad (7)$$

Equation 1 represents effects at the individual-level. The focus is how the slope of *family SES* (π_{1sj}) is adjusted by *school SES* when controlling for other school-level variables (X_{2j} to X_{kj}) in Equation 3, and how the cross-level interaction effect (β_{11j}) between *family SES* and *school SES* is affected by the *Gini index* (γ_{111}) shown in Equation 7. To ease interpretation, I calculate both the predicted intercepts (π_{0sj}) and the predicted digital-use-at-school slopes (π_{1sj}), and present the results in graphs (results are presented in Figure 6.2).

6.5 Results

6.5.1 Comparing Digital Learning Inequalities Between Shanghai and Taiwan

Tables 6.2 and Table 6.3 present results of multilevel analyses testing individual- and school-level effects on Internet literacy in Shanghai and Taiwan, respectively. Before further discussing the results from the tables, we should note that the interclass correlation coefficient (ICC) for the empty model (i.e., a model that only includes the intercept) is .086 for the sample from Shanghai and .042 for the sample from Taiwan. In other words, about 9% and 4% of the variation in the intercept occurs at the school level in Shanghai and Taiwan, respectively. In line with previous literature (Attewell et al. 2003; DiMaggio et al. 2004) and findings from Chapter 4, this suggests that a greater proportion of the variation in digital learning in more economically advanced countries is explained by individual-level characteristics. Having said that, Shanghai's ICC is greater than most newly industrialized Asian economies (ICC is .029 in Hong Kong, .048 in Singapore, .043 in Korea, and .057 in Japan) and Western European countries (ICC is .033 in both Finland and Sweden, .054 in Germany), but like the United States and Canada (ICC is .068 and .106 respectively), and smaller than most lower income countries whose ICCs are beyond .150.

[Table 6.2 and Table 6.3 about Here]

To seek further explanations of the inequality of digital learning, Model 1 presents the average effect of family SES on Internet literacy. For each standard deviation increase in family SES, Internet literacy increases by .319 standard deviations ($p<.01$) in Shanghai and .234 standard deviations ($p<.01$) in Taiwan. After accounting for other important individual-level factors in Model 2, the effect of family SES on Internet literacy remains statistically significant and substantial. Supplementary analyses for Shanghai and Taiwan (not shown in the tables)

suggest that, at the individual student-level, family SES explains 8% and 3%, respectively, of the differences in the effect of Internet literacy.

Model 3 takes the average of school SES into consideration. While school SES does not significantly predict Internet literacy in either society (b=.025, p>.1 in Shanghai; b=−.005, p>.1 in Taiwan), its effect on the slope of family SES is statistically significant (p<.01) and substantial. A one-standard-deviation increase in school SES decreases the effect of family SES on Internet literacy by .173 standard deviations in Shanghai and .130 standard deviations in Taiwan. In Model 4, which includes other school-level factors, the estimated average effect of school SES decreases only slightly, by 21 percent in Shanghai and 15 percent in Taiwan. In Shanghai, it is also worth noting that the effect of school SES on Internet literacy becomes statistically significant (b=.091, p<.01). This indicates that a school's socioeconomic composition predicts its Internet literacy when comparing schools with similar institutional characteristics. Considering the models together, I conclude that family SES significantly affects digital learning, and the effect is stronger in low-SES schools than high-SES schools. Moreover, I find that the effects of SES at both individual- and school-levels are stronger in Shanghai than in Taiwan.

Before moving to the next section, I will discuss the effects of control variables in Model 4. In both Shanghai and Taiwan, male students have a higher level of Internet literacy than their female counterparts. These findings are consistent with previous literature that suggests a large gender digital divide among the Asian societies, with more gender inequality (Ono and Zavodny 2007). And 15-year-old students in a higher school grade than average show higher Internet literacy. Speaking a foreign language at home has no significant impact on Internet literacy. It is noteworthy that family structure affects digital learning differently in

Shanghai and Taiwan. In Taiwan, living in a single-parent family increases levels of Internet literacy over living in a two-parent family. In Shanghai, on the other hand, students from other types of families show lower levels of Internet literacy than those from two-parent families. This disadvantage may reflect to some degree the urban-rural divide, in that many families migrating from poor areas of China to Shanghai lack economic and social support (OECD 2011a:95–96).

Regarding the effects of school-level control variables, there are three notable differences between Shanghai and Taiwan. First, class size is negatively associated with Internet literacy in Shanghai, but not in Taiwan. Second, students who attend a public school rather than a private school have higher Internet literacy, and this effect is stronger in Taiwan than Shanghai. Third, attending a key high school in Shanghai significantly increases Internet literacy relative to other high schools (b=.150), which may indicate that key high schools provide more digital learning opportunities for students. But this advantage is exclusive to students from socioeconomically advantaged families, as digital inequality between higher-SES and lower-SES students is higher among students in key high schools than those in other high schools (b=.130). In Taiwan, by contrast, Internet literacy does not differ between students attending urban public high schools and those from other high schools. To sum up, Table 2 clearly shows that social segregation in schools plays an important part in the digital learning performance of 15-year-olds in Shanghai.

6.5.2 Variation in Digital Learning Within and Between Schools: A Nine-Country Comparison

To further examine the patterns of digital inequality, I plot the predicted Internet literacy against family SES for students in Shanghai, Taiwan, and the other seven societies. In Figure 6.1, the predicted lines are calculated from the results of the separate multilevel models for each country. Each model includes the same individual-level control variables listed in Table 6.1, and four school-level control variables, including class size, teacher shortage, school resource quality, and

public school. Note that the focus is on how the socioeconomic divide in Internet literacy *within schools* differs between high-SES schools and low-SES schools, which are defined by the top decile of schools' average SES and the bottom decile of schools' average SES.

[Figure 6.1 about Here]

It is notable that there are greater variations in the socioeconomic backgrounds of students in the four Chinese societies—Singapore, Shanghai, Taiwan, and Hong Kong—than the other countries, such as Japan and Finland. The Chinese societies also show more digital learning inequality between schools, as the figure clearly shows that the Internet literacy gap by family SES (i.e., the slope of family SES) varies much more for low-SES schools than for high-SES schools. This suggests more social segregation in schools in the four Chinese societies, which would affect digital learning opportunities.

By contrast, there is little variation in the slope of family SES against the average SES of schools in other countries, including Korea, Japan, the United States, Canada, and Finland. Digital learning inequality is lower in Korea and Finland than the rest of the societies, regardless of schools' SES. In the United States, the effect of family SES on Internet literacy is strong for both low-SES and high-SES schools. Supplementary analysis based on the U.S. sample shows that the inequalities of digital learning at the school level are largely explained by students attending public schools versus private schools.

To sum up, the patterns of digital learning inequalities are similar across the four Chinese societies, which are very different from the other five economically developed countries shown in the figure. Family SES plays an important role in the digital learning of students who attend socioeconomically disadvantaged schools in Shanghai, Taiwan, Hong Kong, and Singapore. This finding is very much different from that shown in Appendix 6.1, which states that school SES is

more influential than family SES in predicting student academic achievement in reading.

6.5.3 Variation Within and Between Schools in Digital Learning Across 67 Countries

In this section, I examine how the digital learning inequalities in Shanghai and Taiwan differ from the rest of the world. A related research question is whether income inequality affects digital learning inequality in Shanghai and Taiwan in particular, as well as the other Chinese societies. To show overall trends across the world, I run three-level multilevel modeling which incorporates individual-level (Level 1), school-level (Level 2), and country-level (Level 3) variation in the analyses. As in the previous sections, the focus is still on the patterns of digital learning inequality *within* schools and *between* schools. In each model, I include all individual-level control variables listed in Table 6.1 and four school-level control variables, namely class size, teacher shortage, school resource quality, and public school. At the country-level, I include one variable: the log of the Gini index.[24] Through modeling, I examine how the log of the Gini index affects the relationship between school SES and family SES.

The models are complicated. To explain them more clearly, I only plot the most relevant and useful results. Figure 6.2 presents the effect of the Gini index (*x*-axis) on the level of the effect of school SES on the family SES slope (*y*-axis).[25] In other words, the *y*-axis intersect represents the degree to which the socioeconomic gap in Internet literacy differs between higher-SES and lower-SES schools. The more negative the value, the more variation by school average SES, and the level of within-school digital inequality is smaller in higher-SES schools but much greater in lower-SES schools (see the case of Shanghai, for example, in Figure 6.1). If the value of the *y*-axis intersect is close to zero, on the other hand, it means that the level of within-school

[24] Appendix 6.2 reports the Gini indexes for the 67 countries.
[25] The figure is calculated based on the model in Appendix 6.3.

digital inequality does not substantially differ by school SES (for example, see the case of Finland in Figure 6.1).

[Figure 6.2 about Here]

I find that the Gini index significantly affects the relationship between the slopes of school SES and family SES. Increased Gini index is associated with a decrease in the negative effect of school SES on the family SES slope. This suggests that the effect of family SES on Internet literacy is much the same in high-SES and low-SES schools in countries with higher income inequality. In contrast, family SES clearly does affect Internet literacy differently in high-SES and low-SES schools in those countries with lower income inequality.[26] While Shanghai has a high level of income inequality (.44), the observed effect of school SES on the family SES slope is far below the predicted line. Also, the figure clearly shows that the digital inequality within schools varies more between higher-SES and lower-SES schools in Shanghai than in Taiwan and the other seven countries of interest (highlighted with different symbols and colors). While the Gini indexes of the four Chinese societies are very different from one another, the levels of the effect of school SES on the family SES slope are similar.

6.6 Discussion and Conclusion

Despite the wealth of research on comparative education that centers on the academic performance of students (Chudgar and Luschei 2009; OECD 2010b; Schiller et al. 2002; Schmidt et al. 2015; UNESCO 2015), there is a dearth of research on the effects of family background and school factors on digital learning for students in Shanghai and other East Asian societies. This underexplored research agenda requires more attention, given that the role of ICT in the

[26] Most countries at the bottom left of Figure 6.2 are middle-income or lower middle-income European nations. To name a few (from the left to right): Slovakia (SK), the Czech Republic (CZ), Hungary (HU), Croatia (HR), Montenegro (ME), Lithuania (LT), and Poland (PL).

learning society has becomes more important (Drori 2010; European Commission 1994; Spring 2008).

This chapter examines the inequalities of digital learning *within* and *between* schools, with a focus on 15-year olds in Shanghai and Taiwan. Findings indicate that Shanghai has a higher level of digital learning inequality than Taiwan, which is explained by disparities in Internet access at home between individual students and more school-choice opportunities for parents. As for Taiwanese students, the neighborhood attendance policies at both primary and secondary schools require Shanghai students to attend the public schools that are close to their homes. The parents of Shanghai students are, however, able to choose other public schools by paying a sponsorship fee. Likewise, many parents pursue “key” public schools which have more educational resources or have better records of academic performance (Wu 2012; Ye 2015). These choices contribute to educational inequalities. Indeed, I find that Shanghai students attending “key” public high schools were more Internet literate than other students. More importantly, the effect of family SES on Internet literacy is stronger among students attending “key” public high schools than students in other types of high schools.

This chapter also finds that social segregation in schools is common to the four Chinese societies, including Shanghai, Taiwan, Hong Kong, and Singapore. The SES of students in socioeconomically disadvantaged schools strongly predicts their Internet literacy, but this relationship is much weaker for students attending advantaged schools. This pattern is unique among the four Chinese societies mentioned and does not emerge in other developed countries. In Korea and Finland, for example, the socioeconomic background of students has less influence on their Internet literacy, regardless the type of school the students attend. On the other hand, the SES of students in the U.S. does affect Internet literacy in both lower-SES and higher-SES

schools.

The Shanghai study supports previous literature which suggests that school choice exacerbates social segregation and reproduces educational inequalities (i.e., Zhou et al. 2016). I show that school segregation by SES or class background leads to digital learning inequality. This is in stark contrast to the test results from the 2009 PISA which show SES in Shanghai to have less impact on student academic performance (OECD 2010b).[27]

This chapter also contains important policy implications. While Shanghai and Taiwan, as in other newly industrialized societies like Hong Kong and Singapore, have experienced tremendous economic growth and are front-runners in the development of ICT, this does not guarantee equal treatment of students, particularly those from poor families or in schools with mostly underprivileged students. My research indicates that social segregation in schools means that national development of ICT and promotion of e-learning often advantage only a small number of students and schools. These problems are particularly important for countries that face intense competition among students, more opportunities for school choice, and greater social segregation in schools.

[27] Also see Appendix 6.1, based on author's own analyses from the PISA 2009 data.

Table 6.1: Descriptive Statistics and Variable Descriptions in the Analysis

	Shanghai		Taiwan		
Variable	Mean	SD	Mean	SD	Description / Coding
Individual-level variables:					
Internet literacy	-0.06	0.87	0.03	0.86	Standardized variable based on five online reading activities (Cronbach's a = .78): reading online news, using an online dictionary or encyclopedia (e.g., Wikipedia), searching online information to learn about a particular topic, taking part in online group discussions or forums, and searching for practical information online (e.g., schedules, events, tips, recipes). Response categories from lower to higher values are: "I don't know what it is", "never or almost never", "several times a month", "several times a week", and "several times a day".
Family SES	-0.16	0.92	0.00	0.73	Standardized and PISA-created index of economic, social, and cultural status (OECD 2012), including: parental occupation status expressed as the index of ISEI, parental education in years, and an index of household possessions (e.g., a room for the child, possessions of classical literature, a desk for the child to study at home, the number of books at home).
Male	0.49	0.50	0.50	0.50	1 = male, 0 = female
School grade	-0.48	0.63	-0.32	0.47	Measure of student progress in school. 0 represents students attending school at the same grade as most of other students of the same age within their country. A negative integer (coded -1, -2, etc.) or a positive integer (coded 1, 2, etc.) indicates students are at a grade below or above their expected grade level.
Foreign language use at home	0.02	0.12	0.22	0.41	1 = yes, 0 = no
Single-parent family	0.11	0.31	0.14	0.34	1 = yes, 0 = no. Reference group = two-parent family.
Other family	0.03	0.17	0.03	0.16	1 = yes, 0 = no. Reference group = two-parent family.
School-level variables:					
School SES	-0.17	0.55	-0.01	0.36	Mean of family SES.
Class size	38.64	6.92	39.47	6.11	Mean of a student reported variable representing the number of students attending a language class.
Teacher shortage	0.56	1.36	-0.06	1.29	Standardized variable based on the lack of teachers in four fields (Cronbach's a = .87): science teachers, mathematics teachers, qualified language teachers, and qualified teachers of other subjects. Response categories from lower to higher values are: "not at all", "very little", "to some extent", and "a lot".

(continued)

Table 6.1: (*continued*)

Variable	Shanghai Mean	Shanghai SD	Taiwan Mean	Taiwan SD	Description / Coding
School resource quality	0.26	1.12	0.39	1.12	Standardized variable based on the shortage or inadequacy of seven indicators (Cronbach's a = .87): science laboratory equipment, instructional materials (e.g. textbooks), computers for instruction, Internet connectivity, computer software for instruction, library materials, and audio-visual resources. Response categories from lower to higher values are: "a lot", "to some extent", "very little", and "not at all".
Public school	0.90	0.30	0.62	0.49	1 = yes, 0 = no. Reference group = Private school.
Middle school	0.34	0.47	0.26	0.44	1 = yes, 0 = no. Reference group = Other high school.
Key high school	0.15	0.36	-	-	1 = yes, 0 = no. Reference group = Other high school. Variable omitted for Taiwan.
Experimental model high school	0.13	0.34	-	-	1 = yes, 0 = no. Reference group = Other high school. Variable omitted for Taiwan.
Urban public high school	-	-	0.09	0.29	1 = yes, 0 = no. Reference group = Other high school. Variable omitted for Shanghai
Small town	-	-	0.07	0.26	1 = yes, 0 = no. Reference group = City. Variable omitted for Shanghai.
Town	-	-	0.29	0.46	1 = yes, 0 = no. Reference group = City. Variable omitted for Shanghai.
Large city	-	-	0.27	0.45	1 = yes, 0 = no. Reference group = City. Variable omitted for Shanghai.

Data Source: Programme for International Student Assessment (PISA) 2009.

Note: To preserve cases, multiple imputations (*m* =1) for missing cases are used for individual-level control variables.

Table 6.2: Multilevel Analyses Predicting Internet literacy with Individual- and School-Level Variables: Shanghai Sample

	Model 1	Model 2	Model 3	Model 4
Effects on the Intercept [a]				
Intercept	-.048 (.018)**	-.071 (.020)**	-.032 (.021)	-.109 (.053)*
Male		.063 (.023)**	.063 (.023)**	.063 (.023)**
School grade		.145 (.023)**	.132 (.022)**	.096 (.029)**
Foreign language use at home		-.067 (.092)	-.029 (.092)	-.029 (.092)
Single-parent family		-.055 (.037)	-.050 (.036)	-.059 (.036)
Other family		-.128 (.067)+	-.135 (.067)*	-.133 (.067)*
School SES			.025 (.033)	.091 (.034)**
Class size				-.005 (.002)*
Teacher shortage				.015 (.015)
School resource quality				.046 (.018)*
Public school				.101 (.052)+
Middle school				-.071 (.043)+
Key high school				.150 (.046)**
Experimental model high school				-.123 (.055)*
Effects on the Family SES Slope [a]				
Intercept	.319 (.016)**	.313 (.016)**	.305 (.015)**	.207 (.047)**
School SES			-.173 (.025)**	-.137 (.028)**
Class size				-.002 (.002)
Teacher shortage				.008 (.014)
School resource quality				.026 (.017)
Public school				.051 (.047)
Middle school				.077 (.033)*
Key high school				.130 (.044)**
Experimental model high school				.047 (.048)
Variance components				
Individual-level variance	.6365	.6352	.6354	.6334
Between-school intercept variance	.0290	.0196	.0177	.0113
Between-school family SES variance	.0106	.0086	.0009	< .0001
Log-likelihood	-6,189	-6,164	-6,143	-6,119
$N_{\text{Individual-level}}$	5,109	5,109	5,109	5,109

Note: Number of schools = 151. Standard errors are in parentheses. All coefficients are adjusted by multiple imputations for missing cases in the control variables ($m = 1$). All continuous variables at the individual- and school-levels are grand mean centered.

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

Table 6.3: Multilevel Analyses Predicting Internet literacy with Individual- and School-Level Variables: Taiwan Sample

	Model 1	Model 2	Model 3	Model 4
Effects on the Intercept [a]				
Intercept	.036 (.017)*	-.010 (.021)	.003 (.021)	-.152 (.040)**
Male		.078 (.023)**	.077 (.023)**	.071 (.023)**
School grade		.180 (.031)**	.182 (.031)**	.175 (.052)**
Foreign language use at home		-.015 (.029)	-.012 (.029)	-.011 (.029)
Single-parent family		.095 (.033)**	.095 (.033)**	.099 (.033)**
Other family		-.107 (.069)	-.106 (.069)	-.107 (.069)
School SES			-.005 (.048)	-.086 (.050)+
Class size				.015 (.004)**
Teacher shortage				.027 (.016)+
School resource quality				.047 (.019)*
Public school				.212 (.041)**
Middle school				.030 (.060)
Urban public high school				-.024 (.061)
Small town				-.003 (.059)
Town				-.000 (.036)
Large city				.058 (.036)
Effects on the Family SES Slope [a]				
Intercept	.234 (.018)**	.233 (.019)**	.233 (.019)**	.222 (.046)**
School SES			-.130 (.048)**	-.110 (.052)*
Class size				-.001 (.004)
Teacher shortage				.021 (.020)
School resource quality				.028 (.024)
Public school				-.042 (.051)
Middle school				-.022 (.050)
Urban public high school				-.003 (.071)
Small town				.107 (.072)
Town				.036 (.045)
Large city				.097 (.044)*
Variance components				
Individual-level variance	.6871	.6829	.6830	.6837
Between-school intercept variance	.0244	.0178	.0178	.0096
Between-school family SES variance	.0089	.0105	.0080	.0039
Log-likelihood	-7,045	-7,018	-7,014	-6,991
$N_{\text{Individual-level}}$	5,657	5,657	5,657	5,657

Note: Number of schools = 154. Standard errors are in parentheses. All coefficients are adjusted by multiple imputations for missing cases in the control variables (m = 1). All continuous variables at the individual- and school-levels are grand mean centered.

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

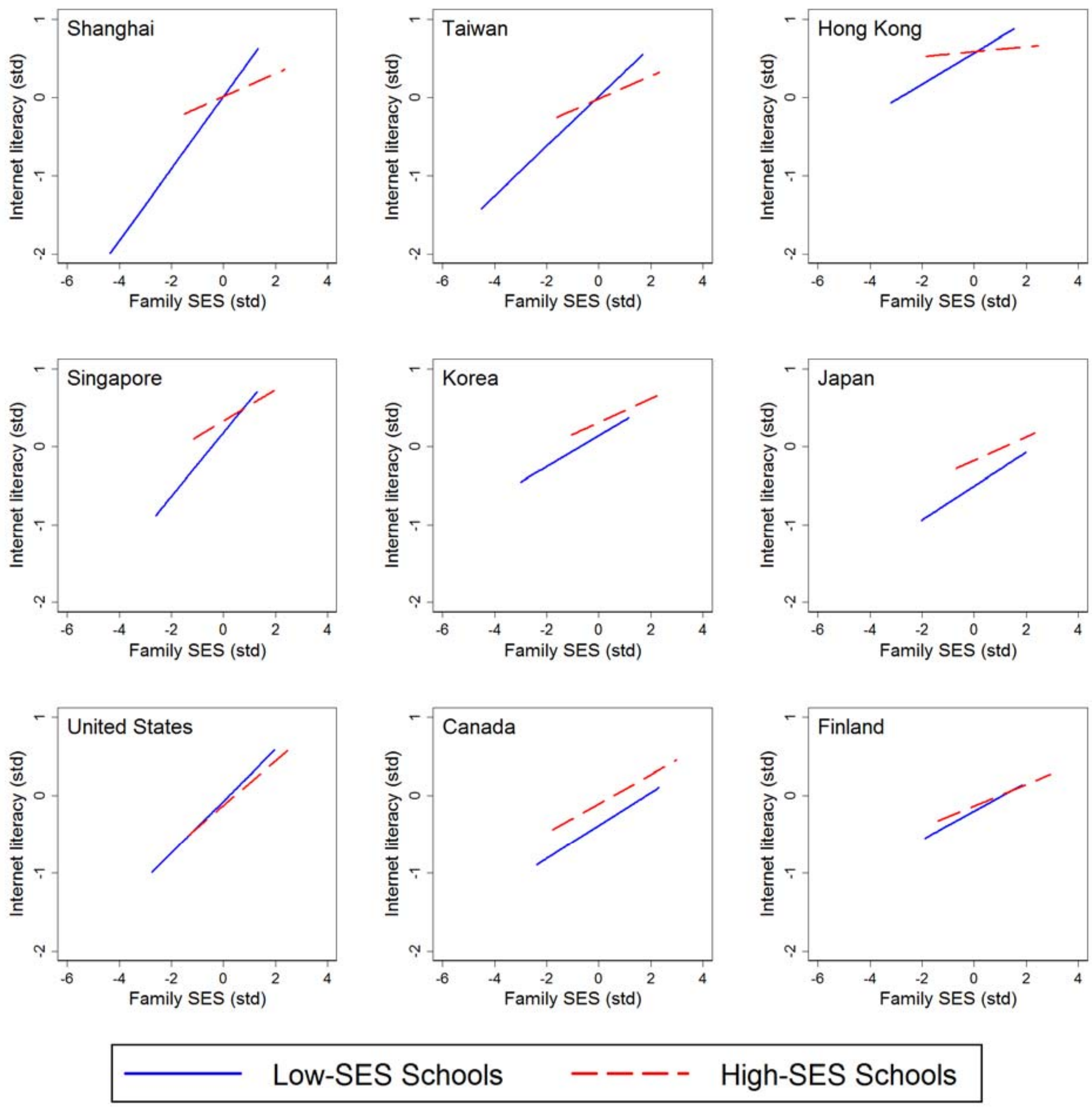


Figure 6.1: Relationship Between Family SES and Internet Literacy: Differential Effects by School SES

Note: The regression lines represent the relationship between family SES and Internet literacy is calculated based on two-level HLM for each of the 9 countries or societies, where students are considered as Level 1 and schools are considered Level 2. Each model includes Level 1 control variables (gender, school grade, foreign language use at home, and family structure) and Level 2 control variables (class size, teacher shortage, and school resource quality). High-SES schools refer to the schools in the top deciles of school SES distribution, and low-SES schools are the schools in the bottom deciles of school SES distribution.

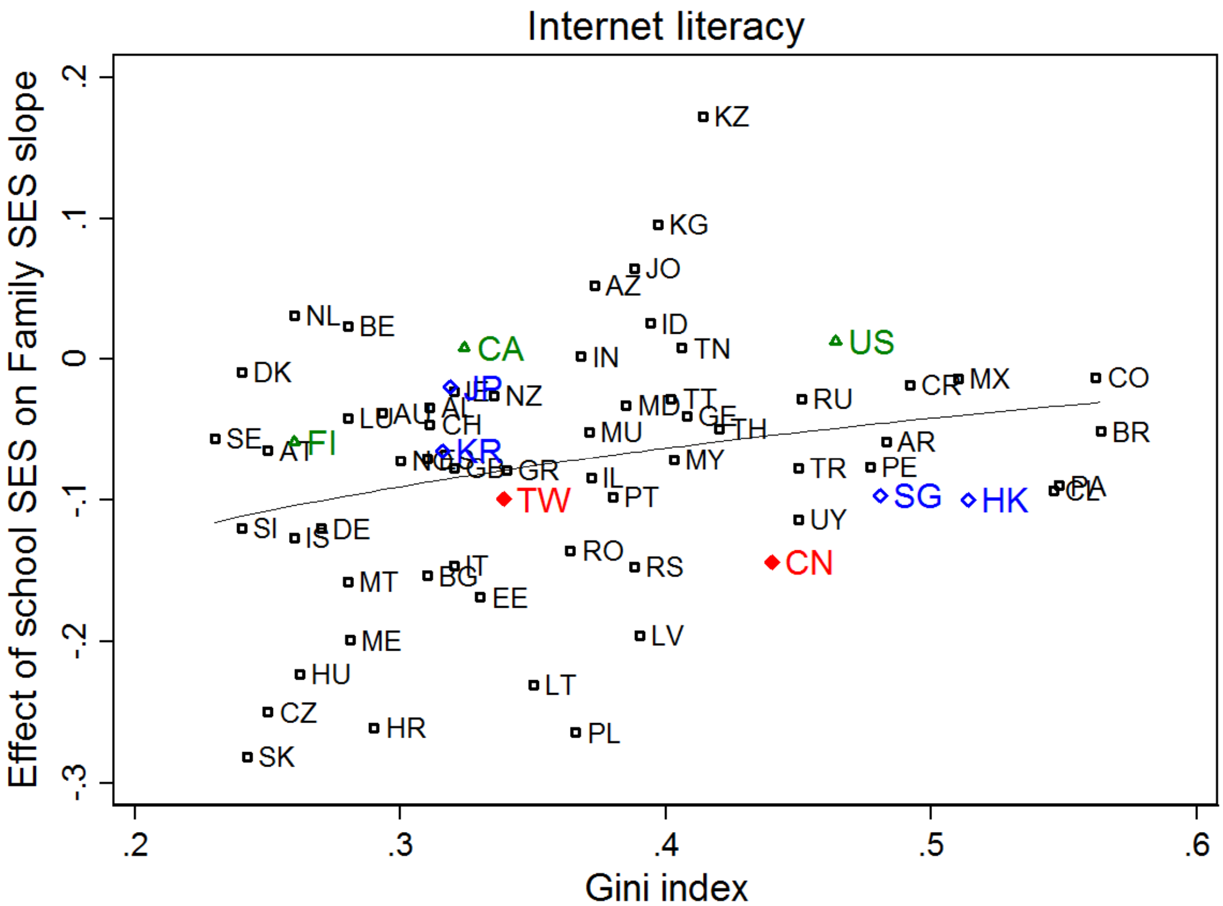
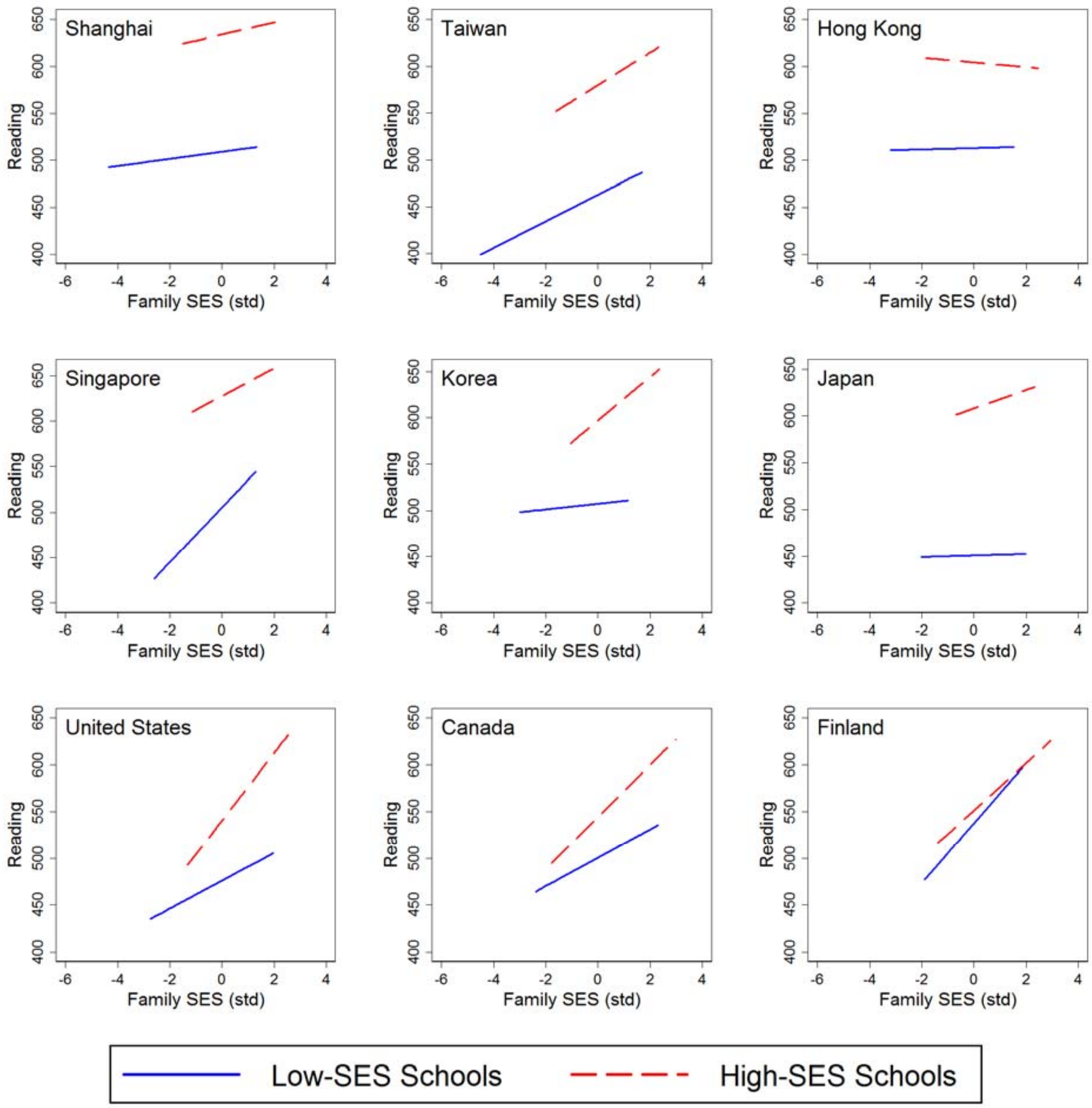


Table 6.2: Effect of Gini Index on the Relationship between School SES and Family SES When Predicting Internet Literacy

Note: The predicted non-linear regression line is based on the result of three-level multilevel modeling in Appendix 6.3. The symbols attached to country acronyms represent the predicted effect of school SES on the family SES slope, adjusted for between-country variance. Among the nine countries highlighted (from the left to the right): *FI* represents Finland, *KR* represents Korea, *JP* represents Japan, *CA* represents Canada, *TW* represents Taiwan, *CN* represents Shanghai, *US* represents the United States, *SG* represents Singapore, and *HK* represents Hong Kong.



Appendix 6.1: Relationship Between Family SES and Reading Performance: Differential Effects by School SES

Note: The regression lines represent the relationship between family SES and reading performance is calculated based on two-level HLM for each of the 9 countries or societies, where students are considered as Level 1 and schools are considered Level 2. Each model includes Level 1 control variables (gender, school grade, foreign language use at home, and family structure) and Level 2 control variables (class size, teacher shortage, and school resource quality). High-SES schools refer to the schools in the top deciles of school SES distribution, and low-SES schools are the schools in the bottom deciles of school SES distribution.

Appendix 6.2: The Gini Index in 67 Countries

	Gini index
Albania (AL)	.31
Argentina (AR)	.48
Australia (AU)	.29
Austria (AT)	.25
Azerbaijan (AZ)	.37
Belgium (BE)	.28
Brazil (BR)	.56
Bulgaria (BG)	.31
Canada (CA)	.32
Chile (CL)	.55
Colombia (CO)	.56
Costa Rica (CR)	.49
Croatia (HR)	.29
Czech (CZ)	.25
Denmark (DK)	.24
Estonia (EE)	.33
Finland (FI)	.26
Georgia (GE)	.41
Germany (DE)	.27
Greece (GR)	.34
Hong Kong (HK)	.51
Hungary (HU)	.26
Iceland (IS)	.26
India (IN)	.37
Indonesia (ID)	.39
Ireland (IE)	.32
Israel (IL)	.37
Italy (IT)	.32
Japan (JP)	.32
Jordan (JO)	.39
Kazakhstan (KZ)	.41
Korea (KR)	.32
Kyrgyzstan (KG)	.40
Latvia (LV)	.39
Lithuania (LT)	.35
Luxembourg (LU)	.28
Malaysia (MY)	.40
Malta (MT)	.28
Mauritius (MU)	.37
Mexico (MX)	.51
Moldova (MD)	.39
Montenegro (ME)	.28
Netherlands (NL)	.26
New Zealand (NZ)	.34
Norway (NO)	.30
Panama (PA)	.55
Peru (PE)	.48
Poland (PL)	.37
Portugal (PT)	.38

(continued)

Appendix 6.2: *(continued)*

	Gini index
Romania (RO)	.36
Russia (RU)	.45
Serbia (RS)	.39
Shanghai (CN)	.44
Singapore (SG)	.48
Slovakia (SK)	.24
Slovenia (SI)	.24
Spain (ES)	.31
Sweden (SE)	.23
Switzerland (CH)	.31
Taiwan (TW)	.34
Thailand (TH)	.42
Trinidad & Tobago (TT)	.40
Tunisia (TN)	.41
Turkey (TR)	.45
United Kingdom (GB)	.32
United States (US)	.46
Uruguay (UY)	.45

Note: Gini index is from UNU-WIDER's (2008) World Income Inequality Database.

Appendix 6.3: Multilevel Analyses Predicting Internet literacy with Individual-, School-, and Country-Level Variables

	Model 1
Effects on the Intercept [a]	
Intercept	-.046 (.526)
School SES	-.103 (.275)
Gini index	.017 (.147)
School SES × Gini index	.073 (.077)
Effects on the Digital Use at School Slope [a]	
Intercept	-.135 (.206)
School SES	-.414 (.174)*
Gini index	.115 (.057)*
School SES × Gini index	.095 (.049)*
Variance components	
Between-country intercept variance	.080
Between-country school SES variance	.020
Between-country family SES variance	.012
Between-country family SES/school SES variance	.008
Between-school intercept variance	.034
Between-school family SES variance	.004
Individual-level variance	.751
Log-likelihood	-594,554
$N_{\text{Individual-level}}$	460,026

Note: Number of countries = 67. Number of schools = 16,561. Standard errors are in parentheses. All coefficients are adjusted by multiple imputations for missing cases in the control variables (m = 1). [a]All models include individual-level control variables (family SES, gender, school grade, foreign language use at home, and family structure) and school-level control variables (class size, teacher shortage, and school resource quality). All continuous variables at the individual-, school-, and country-levels are grand mean centered. Gini index is natural log transformed.

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

Chapter 7:

Conclusions

7.1 Introduction

The use of digital technology in education has continued to grow in the past decade, making digital literacy an increasingly important component of success for students around the world. Despite its growing importance, a digital divide persists between more and less affluent students. This disparity, known as digital learning inequality, has been identified in a wide range of countries throughout the world (Attewell 2001; DiMaggio et al. 2004; Guillén and Suárez 2005; Notten et al. 2009). Despite the wealth of research on the global digital divide (Dutton et al. 2004; Norris 2001), how to explain cross-national variation in the digital learning inequality among school-aged youths received empirically underexplored. In this dissertation, I seek to understand how the digital learning inequalities among 15-year-old students vary in a wide range of countries, using the PISA data. Broadly, I focus on three overarching research questions: How does digital learning differ between students? How does the availability of digital learning vary between schools? What explains cross-national variation in digital learning inequality among students?

In what follows, I summarize the main findings of my dissertation, explain the contributions of the research, and discuss the implications and limitations that should be considered for future research.

7.2 Major Findings

The dissertation reveals several key findings. First, extending previous research based on adult samples (Guillén and Suárez 2005; Hargittai 2002; Robison and Crenshaw 2010), I find national

wealth to be a strong predictor of the digital learning inequalities among teenage students (Chapters 4 and 5). In contrast, the effect of political freedom is small. In line with previous literature, this suggests that democratic governance and political stability affect the digital divide only under a special circumstance that a country's economy is depressed or stagnant (Corrales and Westhoff 2006; Robison and Crenshaw 2010). Despite the importance of this finding, however, it is notable that the inequalities of digital learning still persists among affluent countries. In other words, there is substantial variation in the digital divide among countries with similar levels of national income. This suggests that, net of economic factors, there is a need to consider what other country-level indicators may be influential in the determination of the digital divide.

The second key finding is that both R&D investments and educational expenditures are associated with reducing the inequalities of digital learning between students from various SES groups. Although the size of these effects are modest, they remain statistically significant even when controlling for economic development and individual-level background characteristics. Based on these findings, I suggest that investment in research, innovation, and education that aims at promoting digital learning opportunities for students would reduce digital learning inequality. But these nationally supported objectives should be put within context.

I further find that the effects of R&D investment and educational expenditures matter substantially more for some aspects of digital learning than others (see Chapter 4). To note this difference is important, especially when we are concerned with the global digital divide between more- and less-developed countries. In poor countries, national investments in R&D and education substantially reduce the gap in digital use that is directly related to school-related tasks (i.e., use educational software at home, digital use for schoolwork at home). I show that these

country-level effects moderate the level of digital learning inequality at both student- (Chapter 4) and school-level (Chapter 5). This suggests that there is an opportunity to alleviate this type of digital inequality for these countries, since they have the greatest room to expand their investments in R&D and education (see Appendix 4.2 for examples).

In contrast, increasing R&D investment and educational expenditures in poor nations does *not* reduce, but in fact widens, the gap in online literacy between socioeconomically advantaged versus disadvantaged students. This may be due in part to the lack of strong Internet infrastructure in these countries (Corrocher and Ordanini 2002; Dutton et al. 2004). As Drori (2010) describes, poor countries are "neither pull nor push forces for technology (78)." It is common to see that the laptops and digital appliances donated to schools are outmoded. In addition, the complex interaction of several socio-economic factors such as widespread poverty, lack of social mobility, absence of strong states, and weak labor markets in the developing world may explain this pattern (Chankseliani 2014; Juárez and Gayet 2014; Worden 2014). In Moldova, for example, it has the highest level of educational expenditures as a percentage of GDP per capita among the low-income countries included in my sample. But the strikingly poor economic conditions have further exacerbated the hardships of lower-SES children (Worden 2014). Taken together, I suggest that social inequality, widespread poverty, lack of strong digital infrastructure in the developing world may limit the benefits of national investment in research, technology, and education to students from higher-SES families.

The third key finding is that digital use at school positively predicts digital learning, but this relationship differs greatly between schools and varies across countries (see Chapter 5). For poor countries, the use of digital technology is more beneficial towards students who attend socioeconomically disadvantaged schools than those in socioeconomically privileged schools.

This is because school resources are more unevenly distributed and a great proportion of socioeconomically disadvantaged students have no access to a computer or the Internet at home. For rich countries, on the contrary, the increasing use of digital technology in the classroom does not reduce, but increases, the relative advantage of attending socioeconomically advantaged schools. This supports findings from current research that demonstrates a persistent or "maximally maintained" educational inequality in more-developed countries, despite their high levels of educational expansion and human capital investment (Hannum and Buchmann 2005; Raftery and Hout 1993). As Bourdieu suggests (1984), once learning opportunities become widely accessible to children regardless of their backgrounds, children from privileged families will reproduce their relative advantage by acquiring prestigious educational credentials and taking exclusive practices. Therefore, socioeconomically advantaged and elite students may regard advancing their computer skills and Internet literacy as a key of status distinction and future success, which helps differentiate themselves from other students having digital access without related skills. Related to this, qualitative research in affluent countries finds that schools with more disadvantaged and low-income students tend to use technology for remedial purposes (Attewell 2001; Becker 2000; Warschauer et al. 2004).

The fourth key finding is based on the analysis of Chapter 6, which focuses on the inequalities of digital learning within and between schools in Shanghai and Taiwan. Compared to Taiwan, Shanghai has a higher level of digital learning inequality, which appears both at the student- and school-levels. Two factors may account for this difference: On one hand, there is a greater divide in the access of computers and the Internet at home in Shanghai, where only a small proportion of low-income students have a computer or high-speed Internet access in their households (OECD 2011b). As noted by Drori (2010), China has been “challenged by [its]

enormous population which cripples chances for wide access to ICT yet at the same time both have elite science fields that allow for cutting-edge and world-ranked innovation (76)". On the other hand, the parents of Shanghai students have more school-choice opportunities. Instead of attending the designated public schools that are close to students' residence, they are able to attend other public schools which have more educational resources and better teaching quality (OECD 2011a; Wu 2012; Ye 2015:2; Zhou et al. 2016). This gives some evidence to support educational research that points out that school choice magnifies inequalities in educational settings (Attewell and Newman 2010; Gamoran and Long 2006; Ivanenko 2014).

In addition, Chapter 6 compares the differences between the four Chinese societies (Shanghai, Taiwan, Hong Kong, and Singapore) versus other economically developed or Western countries (Korea, Japan, the U.S., Canada, and Finland). I find that social segregation in schools—defined by the inequality that is due to the differences between schools with different socioeconomic compositions—matters in the four Chinese societies. When considering schools with a majority of socioeconomically disadvantaged students, the family SES of students strongly predicts their digital learning. In contrast, this relationship is much weaker for students attending socioeconomically advantaged or elite schools. With this regard, I suggest that, in these newly industrialized countries and societies, the nationally supported projects on developing "the information society" and promoting "the next 'hot' technology" (Drori 2010:80) would actually give advantage to more affluent students, leading to a widening digital divide between schools.

7.3 Implications

This dissertation makes several key contributions to education and stratification research. First, much research on the educational achievement gap across countries has focused almost exclusively on academic performance. I argue that how students incorporate digital technology

into learning affects preexisting educational inequalities and thus should be examined in its own right. Second, most previous research on the digital divide focuses on individual-level accounts of adults and is conducted primarily in economically advanced countries, especially in the U.S (DiMaggio et al. 2004). I go beyond these studies by focusing on 15-year-old students nested within an economically diverse set of countries. Finally, the existing digital divide literature on adults has focused on general indicators such as GDP per capita and democracy (Robison and Crenshaw 2010); I incorporate two factors that may more directly explain variation in digital outcomes for students—national investment in R&D and secondary education (Norris 2001). With the consideration of how these two factors interact with national income, this dissertation provides new insights into developing new theories that account for the digital learning inequality in the developing world.

Taken together, I believe these contributions provide valuable insight into the determinants of the inequalities of digital learning, which is important because countries seeking to be successful players in the knowledge economy must have digitally literate populations (Spring 2008). I suggest that future quantitative and qualitative research should explore specific projects, policies, or practices that are directly related to equipping the young generation with digital skills—especially economically disadvantaged students. Since digital technology appears likely to be a dominant force in society for the foreseeable future—affecting earnings and other social outcomes—ensuring the next generation is well-prepared with digital skills should be a priority for countries seeking to compete in the global economy. So long as a high level of inequality in these skills persists, social scientists must continue to seek out solutions by exploring various local and national investments which governments can make to help reduce digital learning inequalities.

7.4 Limitations

Despite the above significant findings, there are several shortcomings in this study and I recommend future directions for research. First, since the PISA survey focused overwhelmingly on the most industrialized countries—a common problem of international comparison datasets (Chiu 2010; Park and Kyei 2011)—this research is limited in the number of less-developed countries in the analysis. Future efforts to collect international comparative data will help to reduce this problem. Scholars in the field of comparative education should pay special attention to data from the developing world as this study indicates the importance of looking at the differences in effects between countries of different income levels. Second, note that I am not in a position to ascertain the causal relationship between educational expenditures and the level of digital learning inequality. To establish that connection, future research may benefit from longitudinal studies that examine the change of educational expenditures and the level of digital inequality across time.

References

Agirdag, O., M. Van Houtte, and P. Van Avermaet. 2012. “Why Does the Ethnic and Socio-Economic Composition of Schools Influence Math Achievement? The Role of Sense of Futility and Futility Culture.” *European Sociological Review* 28(3):366–78.

Attewell, Paul. 2001. “The First and Second Digital Divides.” *Sociology of Education* 74(3):252–59.

Attewell, Paul. 2003. “Beyond the Digital Divide.” Pp. 15–34 in *Disadvantaged Teens and Computer Technologies,* edited by P. Attewell and N. Seel. New York: Waxmann.

Attewell, Paul and Juan Battle. 1999. “Home Computers and School Performance.” *The Information Society* 15(1):1–10.

Attewell, Paul and Katherine S. Newman. 2010. *Growing Gaps: Educational Inequality around the World*. New York, NY: Oxford University Press.

Attewell, Paul, Belkis Suazo-Garcia, and Juan Battle. 2003. “Computers and Young Children: Social Benefit or Social Problem?” *Social Forces* 82(1):277–96.

Baker, David, Goesling Brian, and Gerald LeTendre. 2002. “Socioeconomic Status, School Quality, and National Economic Development: A Cross-National Analysis of the ‘Heyneman-Loxley Effect’ on Mathematics and Science Achievement.” *Comparative Education Review* 46(3):291–312.

Batchelor, Batchelor et al. 2003. *ICT for Development Contributing to the Millennium Development Goals: Lessons Learned from Seventeen infoDev Projects*. Washington, DC: The World Bank, Information for Development Program.

Becker, Henry Jay. 2000. “Who’s Wired and Who’s Not: Children’s Access to and Use of Computer Technology.” *The Future of Children* 10(2):44.

Beuermann, Diether, Julian Cristia, Yyannu Cruz-Aguayo, Santiago Cueto, and Ofer Malamud. 2013. “Home Computers and Child Outcomes: Short-Term Impacts from a Randomized Experiment in Peru.” NBER Working Paper Series. (http://www.nber.org/papers/w18818).

Bhanji, Zahra. 2012. “Transnational Private Authority in Education Policy in Jordan and South Africa: The Case of Microsoft Corporation.” *Comparative Education Review* 56(2):300–319.

Binder, Amy J., Daniel B. Davis, and Nick Bloom. 2016. “Career Funneling: How Elite Students Learn to Define and Desire ‘Prestigious’ Jobs.” *Sociology of Education* 89(1):20–39.

Bonfadelli, Heinz. 2002. “The Internet and Knowledge Gaps: A Theoretical and Empirical Investigation.” *European Journal of Communication* 17(1):65–84.

Bourdieu, Pierre. 1984. *Distinction: A Social Critique of the Judgement in Taste*. Cambridge, MA: Harvard University Press.

Bowles, Samuel and Herbert Gintis. 2002. "Schooling in Capitalist America Revisited." *Sociology of Education* 75(1):1–18.

Bradbrook, Gail et al. 2008. "Meeting Their Potential: The Role of Education and Technology in Overcoming Disadvantage and Disaffection in Young People."*Becta*. (http://eprints.lse.ac.uk/4063/1/Meeting_their_potential.pdf).

Broadfoot, Patricia. 2003. "Editorial. Globalisation in Comparative Perspective: Macro and Micro." *Comparative Education* 39(4):411–413.

Buchmann, Claudia and Emily Hannum. 2001. "Education and Stratification in Developing Countries: A Review of Theories and Research." *Annual Review of Sociology* 27:77–102.

Carnoy, Martin and Richard Rothstein. 2013. "What Do International Tests Really Show about U.S. Student Performance?" *Economic Policy Institute*. Retrieved October 31, 2015 (http://www.epi.org/publication/us-student-performance-testing/).

Carr-Chellman, Alison A., ed. 2005. *Global Perspectives on E-Learning: Rhetoric and Reality*. 1st edition. Thousand Oaks, CA: SAGE Publications, Inc.

Carvin, Andy, Chris Conte, and Allen Gilbert. 2001. "The E-Rate in America: A Tale of Four Cities." Pp. 223–42 in *The Digital Divide: Facing A Crisis or Creating A Myth?*, edited by B. M. Compaine. Cambridge, MA: The MIT Press.

Castells, Manuel. 2000. *The Rise of the Network Society*. Blackwell.

Chankseliani, Maia. 2014. "Georgia: Marketization and Education Post-1991." Pp. 277–302 in *Education in Eastern Europe and Eurasia*, edited by N. Ivanenko. London; New York: Bloomsbury Academic.

Chen, Wei-Chu. 2007. "A Study of Information Education and Digital Divide in Taiwan." *Journal of Cyber Culture and Information Society* 13:193–228.

Chiu, Ming Ming. 2010. "Effects of Inequality, Family and School on Mathematics Achievement: Country and Student Differences." *Social Forces* 88(4):1645–76.

Chiu, Ming Ming and Lawrence Khoo. 2005. "Effects of Resources, Inequality, and Privilege Bias on Achievement: Country, School, and Student Level Analyses." *American Educational Research Journal* 42(4):575–603.

Chmielewski, Anna K. 2014. "An International Comparison of Achievement Inequality in Within- and Between-School Tracking Systems." *American Journal of Education* 120(3):293–324.

Choi, Hyaeweol. 1999. “Shifting Human Resources in South Korean Science and Technology.” *Comparative Education Review* 43(2):212–32.

Chudgar, Amita and Thomas F. Luschei. 2009. “National Income, Income Inequality, and the Importance of Schools: A Hierarchical Cross-National Comparison.” *American Educational Research Journal* 46(3):626–658.

Cohen, Joel E., David E. Bloom, Martin B. Malin, and Helen A. Curry. 2006. “Introduction: Universal Basic and Secondary Education.” Pp. 1–8 in *Educating All Children: A Global Agenda*. Cambridge: MIT Press.

Coleman, James S. 1987. “Families and Schools.” *Educational Researcher* 16(6):32–38.

Corrales, Javier and Frank Westhoff. 2006. “Information Technology Adoption and Political Regimes.” *International Studies Quarterly* 50(4):911–33.

Corrocher, Nicoletta and Andrea Ordanini. 2002. “Measuring the Digital Divide: A Framework for the Analysis of Cross-Country Differences.” *Journal of Information Technology* 17(1):9–19.

Cristia, Julián P., Pablo Ibarrarán, Santiago Cueto, Ana Santiago, and Eugenio Severin. 2012. “Technology and Child Development: Evidence from the One Laptop per Child Program.” IZA Discussion Papers 6401, Institute for the Study of Labor (IZA). (https://ideas.repec.org/p/iza/izadps/dp6401.html).

Culp, Katie McMillan, Margaret Honey, Ellen Mandinach, Education Development Center, and Center for Children and Technology. 2003. *A Retrospective on Twenty Years of Education Technology Policy*. U.S. Department of Education.

Dale, Roger. 2005. “Globalisation, Knowledge Economy and Comparative Education.” *Comparative Education* 41(2):117–149.

DeBell, Matthew and Chris Chapman. 2006. *Computer and Internet Use by Students in 2003 (NCES 2006– 065)*. U.S. Department of Education. Washington, DC: National Center for Education Statistics.

DiMaggio, Paul, Eszter Hargittai, Coral Celeste, and Steven Shafer. 2004. “Digital Inequality: From Unequal Access to Differentiated Use.” Pp. 355–400 in *Social Inequality*, edited by K. Neckerman. New York: Russell Sage Foundation.

DiMaggio, Paul, Eszter Hargittai, W Russell Neuman, and John P. Robinson. 2001. “Social Implications of the Internet.” *Annual Review of Sociology* 27:307–36.

Driskell, Nathan. 2014. “NCEE | Global Perspectives: Explaining Taiwan’s Dramatic Improvement in PISA Reading.” *National Center on Education and the Economy (NCEE)*. Retrieved March 13, 2017 (http://ncee.org/2014/10/global-perspectives-explaining-taiwans-dramatic-improvement-in-pisa-reading/).

Drori, Gili S. 2006. *Global E-Litism: Digital Technology, Social Inequality, and Transnationality*. New York, NY: Worth Publishers.

Drori, Gili S. 2007. “Information Society as a Global Policy Agenda: What Does It Tell Us About the Age of Globalization?” *International Journal of Comparative Sociology* 48(4):297–316.

Drori, Gili S. 2010. “Globalization and Technology Divides: Bifurcation of Policy between the ‘Digital Divide’ and the ‘Innovation Divide.’” *Sociological Inquiry* 80(1):63–91.

Dutton, William H., Sharon Eisner Gillett, Lee W. McKnight, and Malcolm Peltu. 2004. “Bridging Broadband Internet Divides: Reconfiguring Access to Enhance Communicative Power.” *Journal of Information Technology* 19(1):28–38.

Education Services Australia. 2012. “National Digital Learning Resources Network.” Retrieved July 29, 2015 (http://www.ndlrn.edu.au/default.asp).

Entwisle, DorisR, KarlL Alexander, and LindaSteffel Olson. 2005. “First Grade and Educational Attainment by Age 22: A New Story.” *American Journal of Sociology* 110(5):1458–1502.

Erichsen, Elizabeth A. and Florin D. Salajan. 2014. “A Comparative Analysis of E-Learning Policy Formulation in the European Union and the United States: Discursive Convergence and Divergence.” *Comparative Education Review* 58(1):135–65.

European Commission. 1994. Europe and the Global Information Society. Brussels, Luxembourg: Office for Official Publications of the European Communities. (http://ec.europa.eu/archives/ISPO/infosoc/backg/bangeman.html).

European Commission. 1995. “Teaching and Learning: Towards the Learning Society.” (http://europa.eu/documents/comm/white_papers/pdf/com95_590_en.pdf).

Fuchs, C. 2008. “The Role of Income Inequality in a Multivariate Cross-National Analysis of the Digital Divide.” *Social Science Computer Review* 27(1):41–58.

Fussell, Elizabeth, Hyunjoon Park, and Carlos Costa Ribeiro. 2010. “Cross-Time and Cross-National Comparisons of the Transition to Adulthood: Brazil, Mexico, and South Korea, 1970-2000.” Dallas, Texas.

Gamoran, Adam. 2001. “American Schooling and Educational Inequality: A Forecast for the 21st Century.” *Sociology of Education* 74:135–53.

Gamoran, Adam and Daniel A. Long. 2006. “Equality of Educational Opportunity: A 40 Year Perspective.” Pp. 3–27 in *Education and Equity: International Perspective on Theory and Policy*, edited by R. Teese, S. Lamb, and M. Duru-Bellat. Springer.

Ganzeboom, Harry B. G., Paul M. De Graaf, and Donald J. Treiman. 1992. "A Standard International Socio-Economic Index of Occupational Status." *Social Science Research* 21(1):1–56.

Goode, Joanna. 2010. "The Digital Identity Divide: How Technology Knowledge Impacts College Students." *New Media & Society* 12(3):497–513.

Government of the Hong Kong SAR. 2012. "Half-Yearly Economic Report 2012." (www.hkeconomy.gov.hk/en/pdf/box-12q2-5-2.pdf).

Grusky, David B. 2001. *Social Stratification : Class, Race, and Gender in Sociological Perspective*. 2nd ed. Boulder, Colorado: Westview Press.

Guillén, Mauro F. and Sandra L. Suárez. 2005. "Explaining the Global Digital Divide: Economic, Political and Sociological Drivers of Cross-National Internet Use." *Social Forces* 84(2):681–708.

Hannum, Emily and Claudia Buchmann. 2005. "Global Educational Expansion and Socio-Economic Development: An Assessment of Findings from the Social Sciences." *World Development* 33(3):333–354.

Hanson, Mark. 2006. "Transnational Corporations as Educational Institutions for National Development: The Contrasting Cases of Mexico and South Korea." *Comparative Education Review* 50(4):625–50.

Hargittai, Eszter. 1999. "Weaving the Western Web: Explaining Differences in Internet Connectivity among OECD Countries." *Telecommunications Policy* 23(10):701–18.

Hargittai, Eszter. 2002. "Second-Level Digital Divide: Differences in People's Online Skills."*First Monday* 7(4). (http://www.firstmonday.org/ojs/index.php/fm/article/view/942/864).

Hargittai, Eszter and Amanda Hinnant. 2008. "Digital Inequality: Differences in Young Adults' Use of the Internet." *Communication Research* 35(5):602–21.

Hargittai, Eszter and Steven Shafer. 2006. "Differences in Actual and Perceived Online Skills: The Role of Gender." *Social Science Quarterly* 87(2):432–48.

Heisig, Jan Paul. 2011. "Who Does More Housework: Rich or Poor? A Comparison of 33 Countries." *American Sociological Review* 76(1):74–99.

Heyneman, Stephen P. and William A. Loxley. 1983. "The Effect of Primary-School Quality on Academic Achievement across Twenty-Nine High- and Low-Income Countries." *American Journal of Sociology* 88(6):1162–94.

Hilbert, Martin. 2010. "When Is Cheap, Cheap Enough to Bridge the Digital Divide? Modeling Income Related Structural Challenges of Technology Diffusion in Latin America." *World Development* 38(5):756–70.

Hill, Paul T. 2010. "Consequences of Instructional Technology for Human Resource Needs in Education." Pp. 137–64 in *Creating a New Teaching Profession,* edited by D. Goldhaber and J. Gornick. Washington, D.C.: The Urban Institute Press.

Imhof, Margarete, Regina Vollmeyer, and Constanze Beierlein. 2007. "Computer Use and the Gender Gap: The Issue of Access, Use, Motivation, and Performance." *Computers in Human Behavior* 23(6):2823–37.

ITU. 2011.*Measuring the Information Society*. Geneva: ITU. (http://www.itu.int/en/ITU-D/Statistics/Pages/publications/mis2011.aspx).

ITU. 2015. *Measuring the Information Society Report*. Geneva: ITU.

Ivanenko, Nadiya, ed. 2014. *Education in Eastern Europe and Eurasia*. London; New York: Bloomsbury Academic.

Jack, Anthony Abraham. 2016. "(No) Harm in Asking Class, Acquired Cultural Capital, and Academic Engagement at an Elite University." *Sociology of Education* 89(1):1–19.

James, J. 2010. "New Technology in Developing Countries: A Critique of the One-Laptop-Per-Child Program." *Social Science Computer Review* 28(3):381–90.

James, Jeffrey. 2009. "Information Technology Use among Individuals in Rich and Poor Countries: The Disappearing Divide." *Telematics and Informatics* 26(4):317–321.

Juárez, Fatima and Cecilia Gayet. 2014. "Transitions to Adulthood in Developing Countries." *Annual Review of Sociology* 40:521–38.

Kim, Sei-Hill. 2008. "Testing the Knowledge Gap Hypothesis in South Korea: Traditional News Media, the Internet, and Political Learning." *International Journal of Public Opinion Research* 20(2):193–210.

Lenhart, Amanda and Pew Research Center. 2015. "Teen, Social Media and Technology Overview 2015." (http://www.pewinternet.org/2015/04/09/teens-social-media-technology-2015/).

Leu, Donald J. et al. 2014. "The New Literacies of Online Research and Comprehension: Rethinking the Reading Achievement Gap." *Reading Research Quarterly* 50(1):37–59.

Leung, Louis and Paul S. N. Lee. 2012. "Impact of Internet Literacy, Internet Addiction Symptoms, and Internet Activities on Academic Performance." *Social Science Computer Review* 30(4):403–18.

Lin, Thung-hong. 2012. "Anything but Online? Digital Divide and Social Consequences of Internet Use in Taiwan." *Taiwanese Sociology* 24:55–97.

Litt, Eden. 2013. "Measuring Users' Internet Skills: A Review of Past Assessments and a Look toward the Future." *New Media & Society* 15(4):612–30.

Livingstone, Sonia and Ellen Johanna Helsper. 2008. “Parental Mediation and Children’s Internet Use.” *Journal of Broadcasting & Electronic Media* 52(4):581–599.

Looker, E.Dianne and Victor Thiessen. 2003. “Beyond the Digital Divide in Canadian Schools: From Access to Competency in the Use of Information Technology.” *Social Science Computer Review* 21(4):475–90.

Margolis, Jane et al. 2003. “The Computer Science Pipeline in Urban High Schools: Access to What? For Whom?” *Technology and Society Magazine, IEEE* 22(3):12–19.

Marshall, Monty G., Ted Robert Gurr, and Keith Jaggers. 2010. “Polity IV Project: Political Regime Characteristics and Transitions, 1800–2009.” Retrieved November 15, 2011 (http://www.systemicpeace.org/polity/polity4.htm).

Martin, Steven P. and John P. Robinson. 2007. “The Income Digital Divide: Trends and Predictions for Levels of Internet Use.” *Social Problems* 54(1):1–22.

Mayer, Susan E. 2001. “How Did the Increase in Economic Inequality between 1970 and 1990 Affect Children’s Educational Attainment?” *American Journal of Sociology* 107(1):1–32.

Ministry of Education. 2006. White Paper on Digital Learning. Taipei, Taiwan: Ministry of Education, Republic of China (Taiwan). (http://english.moe.gov.tw/ct.asp?xItem=1281&ctNode=784).

Mo, Di et al. 2013. “Can One-to-One Computing Narrow the Digital Divide and the Educational Gap in China? The Case of Beijing Migrant Schools.” *World Development* 46:14–29.

Montt, Guillermo. 2011. “Cross-National Differences in Educational Achievement Inequality.” *Sociology of Education* 84(1):49–68.

Murray, Sheila E., William N. Evans, and Robert M. Schwab. 1998. “Education-Finance Reform and the Distribution of Education Resources.” *The American Economic Review* 88(4):789–812.

National Commission on Excellence in Education. 1983. *A Nation at Risk: The Imperative for Education Reform*. Washington, DC: U.S. Government Printing Office.

Natriello, Gary. 2001. “Bridging the Second Digital Divide: What Can Sociologists of Education Contribute?” *Sociology of Education* 74(3):260–65.

Norris, Pippa. 2001. *Digital Divide?: Civic Engagement, Information Poverty, and the Internet Worldwide*. New York: Cambridge University Press.

Notten, Natascha, Jochen Peter, Gerbert Kraaykamp, and Patti M. Valkenburg. 2009. “Research Note: Digital Divide Across Borders—A Cross-National Study of Adolescents’ Use of Digital Technologies.” *European Sociological Review* 25(5):551–60.

OECD. 2010a.*PISA 2009 Results: What Makes a School Successful? – Resources, Policies and Practices (Volume IV).* OECD Publishing. (http://dx.doi.org/10.1787/9789264091559-en).

OECD. 2010b.*PISA 2009 Results: What Students Know and Can Do – Student Performance in Reading, Mathematics and Science (Volume I).* OECD Publishing. (http://dx.doi.org/10.1787/9789264091450-en).

OECD. 2011a.*Lessons from PISA for the United States, Strong Performers and Successful Reformers in Education.* OECD Publishing. (http://dx.doi.org/10.1787/9789264096660-en).

OECD. 2011b.*PISA 2009 Results: Students on Line: Digital Technologies and Performance (Volume VI).* OECD Publishing. (http://dx.doi.org/10.1787/9789264112995-en).

OECD. 2012.*PISA 2009 Technical Report.* PISA, OECD Publishing. (http://dx.doi.org/10.1787/9789264167872-en).

OECD. 2014.*Education at a Glance 2014: OECD Indicators.* OECD Publishing. (http://dx.doi.org/10.1787/eag-2014-en).

Ono, Hiroshi and Madeline Zavodny. 2007. "Digital Inequality: A Five Country Comparison Using Microdata." *Social Science Research* 36(3):1135–55.

Pan, Jin-Gu, Shu-Fen Tseng, and Yu-Fan Lin. 2009. "Extensions of Digital Gini Coefficient: Digital Divides in Taiwan." *Journal of Cyber Culture and Information Society* 16:1–32.

Park, Hyunjoon and Pearl Kyei. 2011. "Literacy Gaps by Educational Attainment: A Cross-National Analysis." *Social Forces* 89(3):879–904.

Pastore, Francesco. 2009. "School-to-Work Transitions in Mongolia." *European Journal of Comparative Economics* 6(2):245–64.

Peter, Jochen and Patti M. Valkenburg. 2006. "Adolescents' Internet Use: Testing the 'Disappearing Digital Divide' versus the 'Emerging Digital Differentiation' Approach." *Poetics* 34(4–5):293–305.

Pietrass, Manuela. 2007. "Digital Literacy Research from an International and Comparative Point of View." *Research in Comparative and International Education* 2(1):1.

Powell, Walter W. and Kaisa Snellman. 2004. "The Knowledge Economy." *Annual Review of Sociology* 30:199–220.

Rabe-Hesketh, Sophia and Anders Skrondal. 2008. *Multilevel and Longitudinal Modeling Using Stata*. College Station, TX: Stata Press.

Raftery, Adrian E. and Michael Hout. 1993. "Maximally Maintained Inequality: Expansion, Reform, and Opportunity in Irish Education, 1921-75." *Sociology of Education* 66(1):41–62.

Rathbun, Amy H., Jerry West, and Elvira Germino Hausken. 2003. *Young Children's Access to Computers in the Home and at School in 1999 and 2000, NCES 2003–036*. Washington, DC: U.S. Department of Education, National Center for Education Statistics.

Raudenbush, Stephen W. and Anthony S. Bryk. 2002. *Hierarchical Linear Models: Applications and Data Analysis Methods*. 2nd ed. Thousand Oaks: SAGE.

Raudenbush, Stephen W. and Robert D. Eschmann. 2015. "Does Schooling Increase or Reduce Social Inequality?" *Annual Review of Sociology* 41:443–470.

Ripley, Amanda. 2014. *The Smartest Kids in the World: And How They Got That Way*. New York, NY: Simon & Schuster Paperbacks.

Robinson, Laura. 2014. "Freeways, Detours, and Dead Ends: Search Journeys among Disadvantaged Youth." *New Media & Society* 16(2):234–251.

Robison, Kristopher K. and Edward M. Crenshaw. 2010. "Reevaluating the Global Digital Divide: Socio-Demographic and Conflict Barriers to the Internet Revolution." *Sociological Inquiry* 80(1):34–62.

Rogers, Everett M. 1995. *Diffusion of Innovations*. Free Press.

Royston, Patrick, John B. Carlin, and Ian R. White. 2009. "Multiple Imputation of Missing Values: New Features for Mim." *The Stata Journal* 9(2):252–64.

Ruiter, Stijn and Frank van Tubergen. 2009. "Religious Attendance in Cross-National Perspective: A Multilevel Analysis of 60 Countries." *American Journal of Sociology* 115(3):863–95.

Schiller, Kathryn S., Vladimir T. Khmelkov, and Xiao-Qing Wang. 2002. "Economic Development and the Effects of Family Characteristics on Mathematics Achievement." *Journal of Marriage and Family* 64(3):730–42.

Schmidt, W. H., N. A. Burroughs, P. Zoido, and R. T. Houang. 2015. "The Role of Schooling in Perpetuating Educational Inequality: An International Perspective." *Educational Researcher* 44(7):371–86.

Sellar, Sam and Bob Lingard. 2013. "Looking East: Shanghai, PISA 2009 and the Reconstitution of Reference Societies in the Global Education Policy Field." *Comparative Education* 49(4):464–85.

Selwyn, N., S. Gorard, and S. Williams. 2001. "Digital Divide or Digital Opportunity? The Role of Technology in Overcoming Social Exclusion in U.S. Education." *Educational Policy* 15(2):258–77.

Shanghai Municipal Education Commission. 2004.*Curricular Plan for Ordinary Primary and Secondary Schools in Shanghai.* Shanghai: Shanghai Education Press. (In Chinese). (www.shmec.gov.cn/web/hdpt/download.php?filename=27.pdf).

Shanghai Municipal People's Government. 2013. "Shanghai Aims for Faster Income Growth." SHANGHAI.GOV. (http://www.shanghai.gov.cn/shanghai/node27118/node27818/u22ai70765.html).

Smith, Jonathan, Zlatko Skrbis, and Mark Western. 2013. "Beneath the 'Digital Native' Myth: Understanding Young Australians' Online Time Use." *Journal of Sociology* 49(1):97–118.

Smith, Michael, Shu-Ling Tsai, Petr Mateju, and Min-Hsiung Huang. 2016. "Educational Expansion and Inequality in Taiwan and the Czech Republic." *Comparative Education Review* 60(2):339–374.

Snow, Catherine. 2002. *Reading for Understanding: Toward an R&D Program in Reading Comprehension*. Santa Monica, CA: RAND Corporation.

Spring, Joel. 2008. "Research on Globalization and Education." *Review of Educational Research* 78(2):330–363.

Tan, Charlene. 2011. "Framing Educational Success: A Comparative Study of Shanghai and Singapore." *Education, Knowledge and Economy* 5(3):155–66.

Tan, Charlene. 2012. "The Culture of Education Policy Making: Curriculum Reform in Shanghai." *Critical Studies in Education* 53(2):153–167.

Tsai, Shu-Ling and Nobuo Kanomata. 2012. "Educational Growth in Taiwan and Japan: Effects of Macroeconomic Change." *Inquires into Humans and Societies – Studies in Sociology, Psychology and Education* 73:79–95.

UNESCO. 2000. *The Dakar Framework for Action: Education for All Meeting Our Collective Commitments*. Paris: UNESCO. Retrieved July 29, 2015 (http://unesdoc.unesco.org/images/0012/001211/121147e.pdf).

UNESCO. 2015. *Education for All 2000-2015: Achievements and Challenges*. Paris: UNESCO. Retrieved July 29, 2015 (https://en.unesco.org/gem-report/report/2015/education-all-2000-2015-achievements-and-challenges#sthash.bfFmEFAV.dpbs).

UNESCO. 2016. "Information and Communication Technologies for Development (ICT4D)." Retrieved July 29, 2015 (http://www.ict4dc.org/).

UNESCO-UIS. 2013. *Information and Communication Technology (ICT) in Education in Five Arab States: A Comparative Analysis of ICT Integration and E-Readiness in Schools in Egypt, Jordan, Oman, Palestine and Qatar*. Montreal, Canada: UNESCO Institute for Statistics. Retrieved July 29, 2015 (http://uis.unesco.org/sites/default/files/documents/information-and-communication-

technology-ict-in-education-in-five-arab-states-a-comparative-analysis-of-ict-integration-and-e-readiness-in-schools-en_0.pdf).

UNESCO-UIS. 2014. *Information and Communication Technology (ICT) in Education in Asia: A Comparative Analysis of ICT Integration and E-Readiness in Schools Across Asia*. Montreal, Canada: UNESCO Institute for Statistics. Retrieved July 29, 2015 (http://uis.unesco.org/sites/default/files/documents/information-communication-technologies-education-asia-ict-integration-e-readiness-schools-2014-en_0.pdf).

UNESCO-UIS. 2015. *Information and Communication Technology (ICT) in Education in Sub-Saharan Africa: A Comparative Analysis of Basic E-Readiness in Schools*. Montreal, Canada: UNESCO Institute for Statistics. Retrieved July 29, 2015 (http://www.uis.unesco.org/Communication/Documents/ICT-africa.pdf).

UNU-WIDER. 2008. "World Income Inequality Database, Version 2.0c, May 2008." Retrieved January 2, 2013 (http://www.wider.unu.edu/research/Database/en_GB/wiid/).

U.S. Department of Education. 1996. "Getting America's Students Ready for the 21st Century: Meeting the Technology Literacy Challenge. A Report to the Nation on Technology and Education." Retrieved July 29, 2015 (http://eric.ed.gov/?id=ED398899).

Vegas, Emiliana and Chelsea Coffin. 2015. "When Education Expenditure Matters: An Empirical Analysis of Recent International Data." *Comparative Education Review* 59(2):289–304.

Vigdor, Jacob L., Helen F. Ladd, and Erika Martinez. 2014. "Scaling the Digital Divide: Home Computer Technology and Student Achievement." *Economic Inquiry* 52(3):1103–1119.

Warschauer, Mark. 2000. "Technology & School Reform: A View from Both Sides of the Tracks." *Education Policy Analysis Archives* 8(4).

Warschauer, Mark, Michele Knobel, and Leeann Stone. 2004. "Technology and Equity in Schooling: Deconstructing the Digital Divide." *Educational Policy* 18(4):562–588.

Wells, John and Laurie Lewis. 2006. *Internet Access in U.S. Public Schools and Classrooms: 1994-2005 (NCES 2007-020)*. U.S. Department of Education. Washington, DC: National Center for Education Statistics.

White House. 2013. "President Obama Speaks on Technology in Schools." Retrieved September 5, 2013 (http://www.whitehouse.gov/photos-and-video/video/2013/06/06/president-obama-speaks-technology-schools#transcript).

Wilkinson, Richard and Kate Pickett. 2009. *The Spirit Level: Why Greater Equality Makes Societies Stronger.* New York: Bloomsbury.

Worden, Elizabeth A. 2014. "Moldova: Challenges and Opportunities." Pp. 47–64 in *Education in Eastern Europe and Eurasia*, edited by N. Ivanenko. London; New York: Bloomsbury Academic.

World Bank. 2015a. "Education Statistics." Retrieved July 20, 2015 (http://data.worldbank.org/data-catalog/ed-stats).

World Bank. 2015b. "Why Use GNI per Capita to Classify Economies into Income Groupings?" Retrieved July 21, 2015 (https://datahelpdesk.worldbank.org/knowledgebase/articles/378831-why-use-gni-per-capita-to-classify-economies-into).

World Bank. 2015c. "World Development Indicators." (http://databank.worldbank.org/data/download/archive/WDI_excel_2015_01.zip).

Wu, Xiaoxin. 2012. "School Choice with Chinese Characteristics." *Comparative Education* 48(3):347–66.

Ye, Hua. 2015. "Key-Point Schools and Entry into Tertiary Education in China." *Chinese Sociological Review* 47(2):128–153.

Zeng, Haijun, Ronghuai Huang, Yuchi Zhao, and Jinbao Zhang. 2012.*ICT and ODL in Education for Rural Development: Current Situation and Good Practices in China.* Beijing, China: UNESCO International Research and Training Centre for Rural Education. (http://indonesiadigitallearning.com/PustakaReferensiBidangPendidikan/story_content/external_files/IDL-Book-35-UNESCO%20-%20ICT%20and%20ODL%20in%20Education%20for%20Rural%20Development.pdf).

Zhong, Zhi-Jin. 2011. "From Access to Usage: The Divide of Self-Reported Digital Skills among Adolescents." *Computers & Education* 56(3):736–46.

Zhou, Yisu, Tianji Cai, and Dan Wang. 2016. "Social Segregation in Hong Kong's Schools: 2000–2012." *Chinese Sociological Review* 48(3):248–270.