AN ANALYSIS OF THE OECD PROGRAMME FOR INTERNATIONAL STUDENT ASSESSENT ON FINANCIAL LITERACY

by

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A dissertation submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economic Education

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ABSTRACT

This study examines the financial knowledge of high school-aged students around the world using the OECD Programme for International Student Assessment (PISA) on Financial Literacy. The PISA Financial Literacy Assessment from 2012 marked the first internationally comparative assessment of the financial knowledge of high school-aged students. Multilevel modeling is used to examine whether or not a gender gap in financial knowledge is present, as well as the role that parents and countries may play in a student's financial knowledge.

The possible gender gap in financial knowledge is first examined. Results indicate that a gender gap may or may not be present within the sample of students. Depending on the subsample used, either a traditional gender gap emerges, whereby male students possess more financial knowledge than female students, or no difference between male and female students is present. The traditional gender gap is present when examining parental characteristics, while examining country-level variables shows no gender gap in financial knowledge.

Characteristics of students' parents are also examined to see what role parents may have in their child's understanding of financial matters. I find that several parental characteristics are associated with a student's financial knowledge. Both the mother's and father's highest levels of schooling, the mother's employment status, discussing money matters with parents on a regular basis, and having a mother live in the student's household are all correlated with a student's financial knowledge. There

is little evidence, however, that parental characteristics contribute to the gender gap in financial knowledge.

Given that the PISA 2012 Financial Literacy Assessment is internationally representative, country-level variables are also examined to determine if there exists a significant correlation between a student's home country and his or her financial knowledge. However, after examining variables such as GDP per capita, the labor force participation rate, and the unemployment rate, I find no evidence of this type of correlation.

Multilevel modeling, or hierarchical linear modeling (HLM), is used to examine the data. To justify the use of multilevel modeling, a methodological comparison is undertaken to determine the best statistical approach for examining the data. Multilevel modeling results are compared to linear regression results across the sample of students. Comparisons of the two methodological approaches indicate that for the PISA 2012 data, multilevel modeling is best suited for the nested structure of the data.

Chapter 1

INTRODUCTION

1.1 Overview of Issues in Financial Literacy

Modern society is ruled largely by financial matters. Whether when making personal financial decisions or when a country makes decisions about how a nation spends its tax revenues, knowledge of financial matters is key to understanding how the world and how the global economy works. Since the global financial crisis of 2007-2009, there has been an increased emphasis on individuals understanding the financial world around them. From classrooms to popular media, individuals are both implicitly and explicitly taught how to conduct themselves in the global, financial economy. From a young age, individuals are taught about the financial world around them through a process known as consumer socialization (Denhardt & Jeffress, 1971; Moschis, 1985; Ward, 1974). This process ensures that individuals learn how to be consumers and learn about the financial world in which they live (Ward, 1974). Consumer socialization can be either an implicit process whereby individuals learn through interaction with the marketplace, or it can be an explicit process where individuals are taught what they should know.

A specific term for what individuals know about money is financial literacy. Financial literacy encompasses both knowledge of financial matters and corresponding financial behavior (Atkinson & Messy, 2012; Hung, Parker, & Yoong, 2009; Organisation for Economic Co-Operation and Development, 2014a). Financial knowledge, on the other hand, refers to the amount an individual knows about financial or money matters. Individuals should be financially literate not only to possess financial knowledge but also to be able to successfully apply that knowledge.

Not only should individuals strive to be financially literate members of society, but policymakers and countries too should aim for financially literate citizenries. Financially literate citizens make better financial decisions, have increased savings rates, and have increased investment rates, among other positive attributes (Atkinson & Messy, 2012; Hastings, Madrian, & Skimmyhorn, 2013; Lusardi & Mitchell, 2011; Nicolini, Cude, & Chatterjee, 2013). Despite the importance of financial literacy, the average adult citizen has been deemed financially illiterate in recent years (Atkinson & Messy, 2012; Lusardi & Mitchell, 2011; Mandell & Klein, 2007; Nicolini et al, 2013). Efforts to measure the financial literacy of citizens around the world have increased since the global financial crisis of 2007-2009, and the results appear grim. Adults in many countries simply do not have a basic understanding of financial or money matters.

As adults around the world prove to be financially illiterate, there has been an increased emphasis on financial education for young people. However, before policies can be designed and implemented, it is important to see how much financial knowledge students have. Therefore, the Organisation for Economic Co-Operation and Development (OECD) administered a Financial Literacy Assessment in 2012 as part of its ongoing Programme for International Student Assessment (PISA). This assessment was designed to measure what teenagers know about financial matters in order to design ways to combat financial illiteracy (OECD, 2014a).

Aside from overall financial illiteracy around the world, a gender gap in financial literacy is often present, where males tend to be more financially literate than females. When testing the financial knowledge of adults around the world, many studies have found a very pronounced gender gap and also worse financial behaviors among adult women (Atkinson & Messy, 2012: Klapper & Panos, 2012; Lusardi, Mitchell, & Curto, 2010; Lusardi, 2011; Organisation for Economic Co-Operation and Development, 2013b). It appears as though this gender gap may or may not begin in high school-aged individuals. Some studies point to a prominent gender gap favoring males (Becchetti, Caiazza, & Coviello, 2013; Lührmann, Serra-Garcia, & Winter, 2012; Varcoe, Martin, Devitto, & Go, 2005), while others found no gender differences or a gender gap favoring females (Hill & Asarta, 2016; Jang, Hahn, & Park, 2014; Walstad, Rebeck, & MacDonald, 2010).

1.2 Purpose of Study

The purpose of this study is to examine the financial knowledge of high school-aged students using the OECD's Programme of International Student Assessment (PISA) 2012 Financial Literacy Assessment. The inaugural administration of the Financial Literacy Assessment as part of the overall PISA Assessment took place in 2012. In fact, 2012 was the first time an international comparison of the financial knowledge of high school-aged students of this magnitude had ever been undertaken. The assessment was administered as a way to not only test the financial knowledge of students around the world but also to have data to draw upon when designing policies to combat financial illiteracy.

This study contains three separate results chapters, each with their own methodology sections. The first chapter examines overall student financial knowledge and whether or not a gender gap exists. The chapter also examines relationships between parental characteristics and student financial knowledge. The second results chapter examines financial knowledge, whether or not a gender gap exists, and whether or not country-level variables influence a student's financial knowledge. Both of these chapters utilize multilevel modeling. The third results chapter uses multilevel modeling results from the previous two chapters and compares them to regression analyses. Results indicate that multilevel modeling is more appropriate for analyzing to the data set and the research questions posed is this study.

1.2.1 Research Questions

Guided by the PISA 2012 Financial Literacy Assessment data and previous research in the field of financial literacy, this study answers the following research questions:

1. How does financial knowledge vary by gender in students around the world?
2. Are parental characteristics related to a student's understanding of financial matters? How are parental characteristics related to gender differences in financial knowledge?
3. Are country-level variables related to a student's understanding of financial matters? Are country-level variables related to gender differences in financial knowledge?
4. In the context of the PISA 2012 Financial Literacy Assessment, are multilevel models or regression analyses better suited for analyzing the data and answering the research questions presented above? Which methodological approach should be used when examining the PISA 2012 data, and why?

A clearer definition of financial literacy and why financial literacy is important follows to give context to the research questions and the study overall.

1.3 What is financial literacy?

Researchers have a difficult time defining financial literacy. In fact, the terms financial literacy, financial knowledge, financial capability, and even economic literacy are frequently used interchangeably to mean the same thing (Hung et al., 2009; Huston, 2010; Jappelli, 2010; Remund, 2010). Often, scholars do not even define the term financial literacy in their research, as researchers believe financial literacy is universally understood (Huston, 2010). Both Huston (2010) and Remund (2010) examined past literature to show that the definition of financial literacy was not clearly defined in most research. Throughout the literature, the term financial literacy refers to consumers' basic understanding of how to use and manage money (Gale & Levine, 2010; Hastings, et al., 2013; Hung et al., 2009). However, the term financial literacy encompasses more than a stock of knowledge. Hung et al. (2009) and Huston (2010) suggest that financial literacy encompasses both knowledge and ability. Some research has even suggested that financial capability might be the more appropriate terminology when discussing what people know about how to use and manage money. Financial capability implies that individuals have adequate knowledge of personal finance to participate successfully in the financial system as well as the ability to do so (Atkinson, McKay, Collard, & Kempson, 2007; Lusardi, 2011).

The President's Advisory Council on Financial Literacy (PACFL) (as cited in Hung et al., 2009) established a comprehensive, conceptual model to better explain financial literacy. Figure 1.1 depicts the model of financial literacy developed by PACFL.

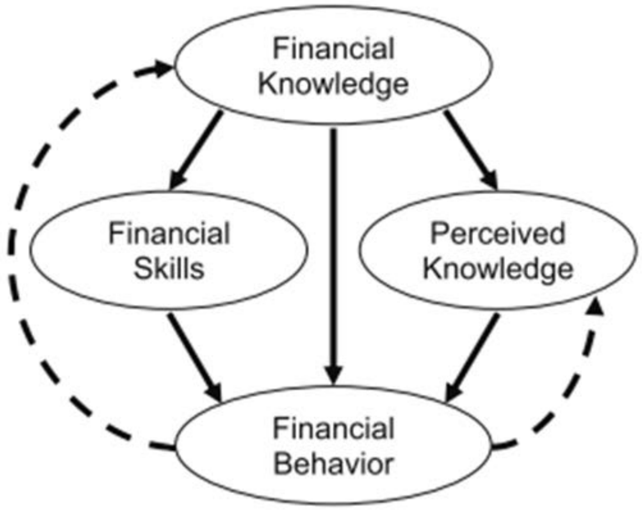

Figure 1.1: Conceptual Model of Financial Literacy

Adapted from “Defining and Measuring Financial Literacy” by A. Hung, A. Parker, and J. Yoong (2009).

Figure 1.1 implies that financial literacy encompasses financial knowledge, financial skills, perceived knowledge, and financial behavior in an interconnected series of relationships. By placing financial knowledge at the top, the model implies that financial literacy begins with knowledge, feeds into perceived knowledge and financial skills, which, in turn, translate into financial behavior. Financial behavior then feeds back to financial knowledge, and the process continues to perpetuate. For example, when students learn about the importance of saving, they not only then have knowledge about savings, but they also ideally have the skills necessary to save and the confidence to do so (perceived knowledge). This capability will then hopefully translate into increased savings (Atkinson & Messy, 2012; Lusardi & Mitchell, 2011). Thus, as the model suggests, financial literacy encompasses financial knowledge, skills, and behaviors, rather than just knowledge (as cited in Hung et al., 2009).

For the purpose of this study, the term financial literacy will be used when describing both an individual's overall understanding of personal finance and his or her corresponding personal financial skills and behaviors. Conversely, the term financial knowledge will refer to just the understanding of financial concepts. Atkinson and Messy (2012) defined financial literacy for adults as "a combination of awareness, knowledge, skill, attitude, and bevahiour necessary to make sound financial decisions and ultimately achieve individual financial well-being" (p. 14). While this definition is comprehensive, it was developed for adults. Since the data used in this study measures the financial knowledge of 15-year-old students, a slightly altered definition is more appropriate. The OECD (2014a) defined financial literacy for the PISA dataset as:

> Financial literacy is knowledge and understanding of financial concepts and risks, and the skills, motivation and confidence to apply such knowledge and understanding in order to make effective decisions across a range of financial contexts, to improve the financial well-being of individuals and society, and to enable participation in economic life (p. 33).

Similar to PAFCL's definition (as cited in Hung et al., 2009), the OECD's definition explains financial literacy as both financial knowledge and corresponding financial behaviors. This definition is also the most applicable for this study because it emphasizes not only the idea of financial literacy but also emphasizes factors contributing to increased financial knowledge. Though in the context of the PISA 2012 dataset the OECD defines the achievement measure as financial literacy, financial knowledge is the more appropriate term for the assessment.

1.4 Rationale for Financial Literacy

Individual and collective success in the global economy depends on a financially literate populace. Individuals who are financially literate are best able to participate in the financial system (Atkinson & Messy, 2012). Atkinson et al. (2007) surveyed research on financial capability, behaviors, and attitudes in the United Kingdom. In their study, the authors showed that increased financial capability (or increased financial literacy) was associated with better financial outcomes for adults, such as increased gross income and an increased number of financial products held. Similar results were found in surveys of American adults. Hastings et al. (2013) examined literature on the financial literacy of American adults and found that those who exhibit higher levels of financial literacy were more likely to make better financial decisions and save more. These results, however, were not country specific. In an extensive international pilot study, the OECD also found a positive correlation between financial knowledge and financial behaviors and a positive correlation between financial behaviors and attitudes toward financial matters (Atkinson & Messy, 2012). These findings came from tests that were part of a pilot study that marked one of the first large scale international analyses of financial literacy. To further examine the importance of financial literacy to individuals, countries, and the global economy, I first examine findings from cross-national studies.

Cross-national studies explain the state of financial literacy by comparing results of citizens in different countries. These studies provide an overview of the financial literacy of adults in a global context. What these studies lack, however, is the ability to explain why individuals in certain countries have more or less financial knowledge. A survey study of eight questions undertaken by the OECD’s International Network on Financial Education (INFE) revealed low levels of adult financial knowledge around the world. The study also showed that less than half of individuals tested were able to exhibit a high level of financial knowledge, defined by the authors as six or more correct answers out of the eight questions. The countries included in the study were Armenia, the Czech Republic, Estonia, Germany, Hungary, Ireland, Malaysia, Norway, Peru, Poland, South Africa, the United Kingdom, Albania, and the British Virgin Islands (Atkinson & Messy, 2012). Similarly, using questions created for the American Health and Retirement Survey (HRS), Lusardi and Mitchell (2011) examined the financial knowledge of adults in Germany, Italy, the Netherlands, New Zealand, Russia, Sweden, and the United States. They found a widespread lack of financial knowledge and showed that decreased retirement savings were associated with low levels of financial knowledge. A more recent study sought to compare the financial knowledge of adults from Canada, Italy, the United Kingdom, and the United States. By combining nationally representative tests of financial knowledge from each country, Nicolini et al. (2013) created an indexed measure of adult financial literacy and used weighted probit modeling to show that financial behaviors such as bank account ownership and increased investment behavior were correlated to increased financial knowledge. Together, these three cross-national studies showed that adults around the world lack financial knowledge. The studies also indicated that countries should be concerned about that lack of financial knowledge because it could lead to lower savings rates and poorer individual financial outcomes (Atkinson & Messy, 2012; Lusardi & Mitchell, 2011; Nicolini et al., 2013).

In recent years, researchers have compiled a group of extensive literature surveys to synthesize international financial literacy research, compare the findings of country-specific studies, and ultimately assess the value of increased financial knowledge. The most extensive review came from the OECD INFE, which pooled and compared nationally representative household surveys of either financial knowledge or financial capability and found low levels of financial knowledge across many countries. Individual countries included in the comparison were Australia, Azerbaijan, Canada, Germany, Indonesia, Ireland, Italy, Japan, the Netherlands, New Zealand, Romania, Russia, Singapore, Sweden, the United Kingdom, and the United States (Hung, Yoong, & Brown, 2012). Subsequently, Hastings et al. (2013) synthesized studies from Chile, Germany, India, Indonesia, Japan, Mexico, the Netherlands, and the United States to examine the long-term effects of increased financial knowledge. More specifically, by linking data and using an intertemporal model of consumer financial decision-making, the authors showed that higher levels of financial literacy were associated with increased financial welfare maximization. Hastings et al. (2013) also showed that not only was financial knowledge important at the individual level, but increased financial knowledge creates significant positive externalities on individual decision-making behavior. As with other studies, the authors found a positive correlation between financial knowledge and financial outcomes, such as increased retirement savings and wealth. Through these syntheses of the literature, it becomes easier to see the importance of increased financial knowledge and/or increased financial literacy around the world.

1.5 Outline of Research

Following this chapter, Chapter 2 discusses the relevant research in financial literacy and financial knowledge, parental influence on financial literacy, and country-level variables that may be related to financial knowledge. Since much of the research on financial literacy and corresponding topics has been conducted in the United States, research for the United States can be found in separate sections than research from other countries.

Chapter 3 provides a detailed description of the data used in the study. The data comes from the OECD's PISA 2012 Financial Literacy Assessment. The assessment was administered to 29,041 students in 4,927 schools in 18 participating countries. In addition to completing the 40-question assessment, students were asked for information about themselves and their family life. School administrators provided information on the schools, and additional country-level information was gathered from the World Bank.

The next three chapters examine the relationships between parental characteristics and student financial knowledge, the relationships between country-level variables and student financial knowledge, and different statistical methodological approaches to examine such relationships. Chapter 4 provides insight into the associations between parent characteristics and student financial knowledge. The parental characteristics of educational attainment, employment status, whether or not the parents live in the household with the student, and whether or not parents discuss money matters with their children are examined. Results show that parents can implicitly influence their child's financial knowledge, as parents' educational attainment and employment status are positively correlated with financial knowledge. The sample of students used in this chapter also exhibits a gender gap favoring male students.

Chapter 5 examines the relationships between country-level variables and student financial knowledge. The country-level variables examined include GDP per capita, the unemployment rate, the overall labor force participation rate, the labor force participation rate for women, and whether or not the country is a member of the OCED. Results from multilevel modeling procedures suggest that country-level variables are not significantly correlated with a student's financial knowledge. The sample used in Chapter 5 was larger than the sample used in Chapter 4 and exhibited no gender gap in financial knowledge.

Chapter 6 compares the previously estimated multilevel models in Chapter 4 and 5 with weighted, cluster-robust regression models using the same dependent and independent variables. The goal of the chapter is to compare the two statistical methodologies to determine which is more applicable to the dataset and research questions. In addition to comparing the estimates themselves, aspects of multilevel modeling and linear regression are discussed. The comparisons indicate that multilevel models are more appropriate for the PISA dataset and research questions.

This dissertation adds to the growing body of literature on the financial knowledge and financial literacy of high school-aged students. Results indicate that parental characteristics are correlated with student financial knowledge, but country-level variables are not associated with student financial knowledge. The subsample used in Chapter 4 reveals a gap in financial knowledge favoring male students, while the larger sample examined in Chapter 5 reveals either a statistically significant difference between the financial knowledge exhibited by male and female students or no difference in male and female scores, depending upon the weighting strategy used. Finally, comparisons of multilevel and regression models show that multilevel models are more appropriate for analyzing the PISA dataset and answering this dissertation's research questions.

Chapter 2

LITERATURE REVIEW

This chapter reviews previous studies on international financial literacy, the importance of financial literacy, whether or not a gender gap in financial literacy exists, and factors related to financial literacy. In sections 2.1 – 2.3, the chapter first discusses important findings both internationally and in individual countries, as well as for both adults and high school-aged students. Next, the importance of financial literacy is discussed. Sections 2.4 and 2.5 discusses literature regarding the gender gap in financial literacy to determine whether gender differences in financial literacy exist but also to see why a gender gap may or may not exist. Finally, Section 2.6 examines how parental influence may be related to financial knowledge as well as how country-level variables may be related to financial knowledge.

2.1 International Financial Literacy at the Country Level

Various countries have sought to measure their citizens' financial knowledge. Overall results showed low levels of adult financial knowledge around the world. For example, a study of British adults found they lacked knowledge about managing money, planning ahead, choosing financial products, and staying informed about financial matters (Atkinson et al., 2007). Klapper and Panos (2011) used three questions of financial knowledge and found low levels of financial literacy in Russia. Using the term economic literacy rather than financial literacy when examining 55 industrialized countries, Jappelli (2010) showed that economic literacy and PISA math and reading scores were positively correlated. Rather than simply indicating the state of financial knowledge within a specific country, most of the work regarding financial knowledge within a country has sought to examine the relationships between financial knowledge and financial outcomes.

2.1.1 Individual Country Studies

In addition to measuring financial knowledge, much of the international financial literacy research has focused on examining the relationships between financial knowledge and financial outcomes within individual countries. For example, an Australian study used the 2003 ANZ Survey of Adult Financial Literacy and found that Australian citizens lack financial knowledge. The authors regressed financial knowledge on various demographic characteristics to examine who lacked financial knowledge and found relationships between increased financial behaviors and financial knowledge (Worthington, 2006). A similar report from the Reserve Bank of New Zealand synthesized results from two large surveys and showed a lack of financial knowledge and poor financial behaviors among adults in New Zealand (Widdowson & Hailwood, 2007). Hastings and Tejeda-Ashton (2008) showed that Mexican citizens with low levels of financial literacy were less likely to participate in the country's social security system. Behrman, Mitchell, Soo, and Brown (2010) used an instrumental variables approach on data from Chile and found that high levels of financial literacy were directly and positively correlated with wealth accumulation. In the Netherlands, a test of financial knowledge and financial behaviors was administered to a sample of 1,508 adults to determine the relationship between financial literacy, retirement planning, and wealth. The study used a set of five financial knowledge questions to create an indexed measure of financial literacy to use in subsequent regressions. The authors found that increased financial literacy was positively correlated with increased wealth and better retirement planning (van Rooij, Lusardi, & Alessie, 2012). Russia sought to measure the financial literacy of its citizens during the financial crisis of 2003-2008. In this study, Klapper, Lusardi, and Panos (2012) used probit and instrumental probit models and found that increased financial literacy was correlated with bank account ownership. An earlier study of Russian adults used a three-question financial knowledge assessment and showed low levels of financial knowledge overall, but that those who tended to plan better for retirement had more financial knowledge (Klapper & Panos, 2011).

Additional studies have sought to determine best strategies to combat financial illiteracy. Orton (2007) recognized that Canada could learn from the experiences of other countries, and especially the findings from the OECD. The author noted that Canada could benefit from policies such as increasing the amount of financial education programs. Widdowson and Hailwood (2007) used a previous finding that individuals in New Zealand were financially illiterate to demonstrate the importance of financial knowledge for their citizens by calling for increased financial education programs.

2.2 High School Financial Literacy Around the World

Developed countries around the world have sought to test the financial knowledge of high school students using financial knowledge assessments. Results from most of these countries indicate that high school students lack financial knowledge. In Germany, high school students were shown to have little financial knowledge or interest in financial matters before taking a financial education course (Lührmann et al., 2012). Using the 2006 Korean National Financial Literacy Test

Survey for Adolescents, South Korean high school students scored on average just below 50% (Sohn, Joo, Grable, Lee, & Kim, 2012). When examining the effects of financial education on the investment attitudes of Italian high school students, Becchetti et al. (2013) found that students in both control and treatment groups lacked financial knowledge. High school students in New Zealand showed very low average financial knowledge scores as measured by the *Financial Fitness for Life—High School* (*FFFL-HS*) test, especially when controlling for factors such as math ability and socioeconomic status (Cameron, Calderwood, Cox, Lim, & Yamaoka, 2014). Taken together, these studies show that students worldwide generally lack financial knowledge.

Other countries sought to compare the performance of their students to other students around the world. For example, using the *FFFL-HS* test norming results, Jang et al. (2014) compared the financial knowledge of South Korean high school students with that of their American counterparts. They found that Korean students scored higher than those American students without any financial education but below American students who had received formal financial education. When comparing high school and college students from New Zealand, Japan, and the United States using the *FFFL-HS* Assessment, Cameron, Calderwood, Cox, Lim, and Michio (2013) found that Japanese students scored, on average, the highest at 56.7% correct, while New Zealand students scored 45.3% correct, and American students had the lowest average score at 44.8% correct. In a similar comparison of the financial knowledge of high school students in Belarus, Japan, and the United States, Borodich, Deplazes, Kardash, and Kovzik (2010) found that Japanese students had the highest level of financial literacy while their Belarusian and American counterparts had very similar, lower levels of financial literacy. The study was completed using means, correlation analyses, and hypotheses testing.

2.3 Financial Literacy in the United States

Across a variety of age ranges, research using both survey data and knowledge tests has indicated that American adults do not comprehend the financial world around them. For example, using a test administered by the Federal Reserve to American households, Hilgert, Hogarth, and Beverly (2003) summarized the financial knowledge and financial behaviors of Americans with low levels of financial knowledge, despite families reporting relatively good financial behaviors. Other similar studies have shown that, overall, American adults are financially illiterate (Hastings et al., 2013; Lusardi & Mitchell, 2007). And, arguably more important, the authors have found that a lack of financial knowledge is correlated with poor financial decision-making. Hilgert et al. (2003) used the Federal Reserve's Survey of Consumers. The authors showed not only that American adults lack financial knowledge but also that there is a direct link between low levels of financial knowledge and poor financial behaviors, thus showing that American adults are financially illiterate.

Annamaria Lusardi and Olivia Mitchell have conducted much of the research on the financial knowledge of American adults in recent years. In the early 2000s, Lusardi and Mitchell (2011) created three questions to include in the 2004 US HRS survey of adults over 50 years old. These questions covered the topics of interest compounding, inflation, and risk diversification (Lusardi & Mitchell, 2011).[1] These

[1] The questions are presented in their entirety in Appendix A.

same questions were subsequently included in the National Longitudinal Survey of Youth (NLSY), RAND's American Life Panel (ALP), and the National Financial Capability Study (NFCS) to measure the financial literacy of various populations (Lusardi & Mitchell, 2014). In the 2004 HRS data, only 34.3% of American adults were able to answer all of the financial knowledge questions correct (Lusardi & Mitchell, 2011). Lusardi and Mitchell restricted the same sample to 785 women and found a positive statistical relationship between retirement planning and financial knowledge. Also, in an earlier study using regression analysis, Lusardi and Mitchell (2008) found that those individuals who answered the risk diversification question correctly were more likely to plan for retirement.

Findings from the NFCS also showed that Americans have low levels of financial knowledge. Only 10% of the sample was able to answer all of the financial literacy questions correctly (Lusardi, 2011). The NLSY was intended to track the behaviors and knowledge of students beginning in adolescence (when they were between the ages of 12-17) and subsequently obtain data from different points in their adult lives. NLSY added financial literacy questions in 2007-2008, when the individuals in the sample were between the ages of 23 and 28 years old. Results from the NLSY were more positive, as 79% of the 7,417 participants were able to answer the interest rate question correctly, 54% answered the inflation question correctly, and 47% answered the risk diversification question correctly (Lusardi et al., 2010). Yet, the fact that results using the same set of three questions varied across different samples brings into question the appropriateness of the questions to measure financial knowledge. Lusardi and Mitchell (2011) argue that these three questions measure financial literacy, when the questions actually measure financial knowledge.

Schmeiser and Seligman (2013) questioned the validity of the three questions that were included in the HRS study. Using regression analysis, the authors determined that answering the three questions correctly had no relationship to wealth over time. Thus, they did not truly measure financial knowledge. While these questions may not be the best measure of an individual's true financial knowledge, they do point to widespread lack of financial knowledge in recent years in the United States.

2.3.1 Importance of Financial Literacy – Financial Behaviors

The relationship between adults' financial literacy and their financial behaviors is important. Since the financial crisis, both the relationships between financial literacy and financial behaviors, as well as the relationship between financial knowledge and corresponding financial behaviors, have been extensively examined in the United States. Using the 2001 University of Michigan's Survey of Consumers, Hilgert et al. (2003) effectively showed that individuals' increases in financial knowledge positively affected their money management and personal investment abilities. In the survey, a total of 1,004 individuals were asked about their financial behaviors related to cash flow, credit use, saving, and investing. In addition, individuals completed a true/false quiz to assess their financial knowledge. The authors then created indices of financial behaviors and conducted correlation analyses between the behavior indices and financial knowledge. The authors found positive correlations between knowledge and the indices, indicating that the higher one's knowledge score, the higher one's expected financial behavior index values (Hilgert et al., 2003). Using three logit models looking at cash flow behavior, savings behavior, and investment behavior, the authors examined cash flow, savings, and investment behaviors. They found a positive relationship between all of these financial behaviors and increased knowledge. A phone study in the United States revealed that attending employer-based financial education programs led to increased retirement savings and increased participation in 401k plans (Bernheim & Garrett, 2003). Using the 2012 NFCS, Wagner (2015) found mixed results of increased financial literacy on short-term behaviors, such as rotating credit card debt, but positive relationships between increased financial literacy and long-term financial behaviors, such as saving for retirement. Across a variety of sources, there was a link between financial knowledge and financial outcomes such as increased retirement savings and increased wealth (Hastings et al., 2013; Wagner, 2015; Xiao & O'Neill, 2016).

The influence of greater levels of financial knowledge is not limited to individuals, as increased financial knowledge also influences communities (Brown, Ivković, Smith, & Weisbenner, 2008; Lachance, 2014). Using data from the 2009 and 2012 NFCS, Lachance (2014) examined the influence of higher levels of financial literacy on neighborhoods. The study used neighborhood average levels of educational attainment as a proxy for the social effects financial literacy could have on a community. The author showed a positive relationship between a neighborhood's education level and financial literacy as well as a positive relationship with financial behaviors. Brown et al. (2008) used an instrumental variables approach to measure the relationship between an individual's stock market participation and his or her community's level of stock market participation. The authors found that a 10 percentage point increase in community stock market participation was associated with a four percentage point increase in individual stock market participation. The study was large, examining close to 400,000 observations for over 85,000 taxpayers in a variety of major metropolitan areas. While the finding was a reverse trend, whereby community effects impacted individual effects, the authors argued that an increase in stock market participation on the individual level then lead to increased discussion of the stock market and increased community participation, leading to somewhat of a snowball effect (Brown et al., 2008). Thus, higher levels of financial knowledge likely have spillover effects by encouraging other community members to be better engaged in their financial lives.

Not all studies have found a link between increased financial knowledge or financial literacy and financial behaviors. Using logit regression estimation with a small sample of households from the state of Indiana, Alhenawi and Elkahl (2013) found no correlation between financial knowledge and individuals completing long-term financial planning, despite the fact that respondents scored close to 75% correct on the seven financial knowledge questions used in the study. However, since the sample was representative of only one state, and was not well defined, the study cannot be generalized to larger populations. Collins (2012) used difference-in-difference (DID) models and found no relationship between financial education programs and increased savings. However, as in Alhenawi and Elkahl's study, Collins estimated his model using a small sample of 144 individuals. An examination of the longitudinal HRS data showed no relationship between financial knowledge scores and overall wealth (Schmeiser & Seligman, 2013). The study, however, attempted to show that the questions asked on the HRS survey were not a good measure of financial literacy but not that financial literacy was unimportant. Overall, results from tests of Americans' financial knowledge indicate that being financially literate can improve financial behaviors.

2.3.2 Importance of Financial Literacy – Financial Decision-Making

Increased financial knowledge is also important in other decision-making processes at both the individual and social levels. For individuals, it is important that they know what decisions need to be made in order to maximize their welfare and also how to make those decisions. Using the Survey of Participant Finances (SPF) and the Survey of Financial Attitudes and Behaviors (FAB) administered to TIAA-CREF participants in 2001, Ameriks, Leahy, and Hall (2003) showed that the propensity to plan for retirement was related to increases in net worth and wealth. Through regression analyses, the authors showed that those who exhibited more control over their finances tended to have more wealth. The finding contradicts those of Bernheim, Skinner, and Weinberg (2001), who revealed no link between wealth and retirement planning using the Panel Study of Income Dynamics and the Consumer Expenditure Survey. Using an intertemporal model of consumer financial decision-making, Hastings et al. (2013) found that individuals with higher levels of financial literacy were able to better maximize their own welfare, or make themselves better off in the long run. Furthermore, not only is financial knowledge for individual outcomes, but increased financial knowledge has been shown to have spillover effects on decision-making as well. Lusardi and Mitchell (2014) suggested that targeting those individuals with low levels of financial literacy could prevent future financial crises. Decision-making is an important part of financial literacy, and one that has been shown to have both individual and social effects.

2.3.3 Financial Literacy among Postsecondary Students in the United States

Some research regarding the lack of financial literacy in Americans examined college-aged students, as it is the time in most young adults' lives where they first experience financial independence (Cude & Kabaci, 2012). On a 20-question financial knowledge test, 407 college freshmen at Texas A&M University scored an average of 34.8% correct. In fact, 92% of the respondents scored less than 60% correct (Avard, Manton, English, & Walker, 2005). A follow-up study using the same data found similar results (Manton, English, Avard, & Walker, 2006). Using a test of financial knowledge of over 1,800 students from 14 different universities, Chen and Volpe (1998) showed average performance on the test was less than 53% correct.

Researchers have also been interested in testing the link between financial knowledge and financial behaviors among college students. For example, Robb and Sharpe (2009) used a double hurdle model to first regress financial knowledge on whether or not college students would carry a revolving balance on a credit card and then, if applicable, how much that balance would be. Unfortunately, there was no statistical link between financial knowledge and carrying a revolving credit card balance (Robb & Sharpe, 2009). Hancock, Jorgensen, and Swanson (2013) used data from American college students in six states to show a small link between knowledge and the likelihood of having more credit cards. The data also revealed an average score of 60% on a 27-question multiple choice financial knowledge assessment. While no large scale, comparative studies of financial literacy at the college level exist, it is clear that a lack of financial knowledge exists at the college level.

2.3.4 High School Findings in the United States

Findings at the high school level in the United States are very similar to college findings but used different analyses. Through measuring the effects of financial education programs, many studies found relationships between financial knowledge and financial literacy. The plethora of programs vary in content, application, and students reached at the high school level; it is not surprising then that measures of high school financial education program effectiveness also varied (Harter & Harter, 2009). Overall, however, most programs indicate at least short-term, positive effects on financial knowledge. The National Endowment for Financial Education (NEFE) High School Financial Planning Program was one of the first high school programs studied. Boyce and Danes (1998) evaluated the program using data from 4,107 students in the 1997-1998 school year. They determined, using a three-question financial knowledge assessment that financial knowledge of high school students increased as a result of the NEFE program. The program was assessed again in the 2003-2004 academic year, and similar results were reported (Danes, 2004). Many studies of financial literacy using tests of financial knowledge such as the *FFFL-HS* test have shown that high school students lack financial knowledge (Butters, Asarta, & McCoy, 2012; Walstad et al., 2010).

The research focus at the high school level is on financial education programs that can help to increase financial knowledge in order to combat financial illiteracy and negative financial behaviors later in life. Considerable work done by practitioners in the United States has focused on increasing student knowledge and financial behaviors through the use of different personal finance programs and curricula. In Milwaukee schools, Butt, Haessler, and Schug (2008) found that the *FFFL-HS* curriculum led to large increases in students' personal finance knowledge when examining pre- and post-test data. Students in Los Angeles schools were exposed to a pseudo-randomized experiment using Junior Achievement's "Finance Park." The students were randomly assigned an adult persona and had to make every day financial decisions as if they were that adult. With this program, the students were 35% more likely to successfully complete a budgeting exercise, thus proving an increase in both financial knowledge and financial skills (Carlin & Robinson, 2012). Asarta, Hill, & Meszaros (2014) showed that students who completed a one-semester personal finance course called *Keys to Financial Success* had gains in their financial knowledge scores. These results came from students in Delaware, New Jersey, and Pennsylvania and were limited to the short-term effects of financial education. However, some programs have not found positive effects of youth financial education in the long run (Mandell & Klein, 2009; Peng, Bartholomae, Fox, & Cravener, 2007; Tennyson & Nguyen, 2007). More research needs to be conducted at the high school level in order to determine the effect of financial education on financial knowledge and financial literacy.

2.4 Gender Gap in Financial Literacy

A great deal of research has focused on the relationship between financial knowledge and gender. Using tests of financial knowledge, many authors have found a gender gap in the financial knowledge of adults, whereby males have more knowledge than females (Atkinson & Messy, 2012; Lusardi et al., 2010; Lusardi, 2011; OECD, 2013b). However, this research has not been able to find a concrete reason as to why this gender gap exists (Fonseca, Mullen, Zamaroo, & Zissimopolus, 2012). The knowledge gender gap does impact financial decisions, as men and women tend to make different financial choices (Atkinson & Messy, 2012; Klapper & Panos, 2011). This research proves gender differences in financial knowledge and financial behaviors.

2.4.1 Gender Gap in Adults – International Findings

Tests of financial knowledge have been administered to adults in many developed countries around the world, and gender differences in financial literacy have been extensively examined. At the college level in Malaysia, female students were found to have less financial knowledge than male students using t-tests and path analyses of 2,500 students (Falahati & Paim, 2011). In all countries examined except for Hungary, Atkinson & Messy (2012) found that, on average, men scored higher than women on tests of financial knowledge. Countries examined within the study included Albania, Armenia, the Czech Republic, Estonia, Germany, Hungary, Ireland, Malaysia, Norway, Peru, Poland, South Africa, the United Kingdom, and the British Virgin Islands. A study using panel data and instrumental variables in probit models found women in the Russian Federation were less financially literate than men. To model financial literacy for individuals answering a simple, four question assessment of financial knowledge, principal component analysis was used to show low levels of financial literacy, especially in women (Klapper, Lusardi, & Panos, 2013). Elsewhere in Europe, similar findings hold. In Germany, Italy, Japan, the Netherlands, and Sweden, adult women were found to have lower levels of financial literacy than adult males (Hung et al., 2012; OECD, 2013b). These findings come from OECD reports, which examined the percent correct on various assessments of financial knowledge and did not statistically examine further explanations as to why it might be the case.

2.4.2 Gender Gap in Adults – United States

In the United States, a prominent gender gap in financial literacy appears to be prevalent, whereby women are less likely to be financially literate than males. The trend begins often in college, where female students have been found to have less financial knowledge than their male peers. For example, male students at Texas A&M were found the have higher average mean scores on a test of financial knowledge than female students (Avard et al., 2005; Manton et al., 2006). Chen and Volpe (1998) used ANOVA and logistic regressions to show that college men consistently outscored college women on tests of financial knowledge. Following up on these findings, Chen and Volpe (2002) found a gender gap in achievement for 924 college students, whereby men scored higher than women on a test of financial knowledge. The finding held for 22 of the 36 questions on the assessment, and gender, specifically being a male, was a significant and positive predictor in subsequent regression analyses of financial knowledge. In all of these studies, students were given short tests of financial knowledge. The gender gap in financial knowledge then continued into adulthood. In tests of financial knowledge, American women were found to be less likely to answer financial questions correctly and were more unsure of the answers they did choose than males (Lusardi et al., 2010; Lusardi, 2011). Furthermore, when controlling for other factors such as neighborhood and socioeconomic status, women were still found to be less financially literate than men (Lachance, 2014).

Many have posited why the gender gap exists, but there has been very little success in determining concrete reasons for the gender gap in financial literacy. Fonseca et al., (2012) attempted to explain the gender gap by examining RAND American life panel data about financial knowledge using Blinder-Oaxaca decompositions. Here, the authors found, once again, a traditional gender gap where males outscored females, but the gap could not be attributed to individual characteristics of men and women. The authors postulated that the gender differences might not be in inherent traits but perhaps in the differences in household specialization, whereby men tend to specialize in financial matters and women in other household functions (Fonseca et al., 2012).

Studies examining only samples of American women have also attempted to explain possible factors contributing to financial differences between men and women. For example, Mahdavi and Horton (2014) surveyed alumni from Smith College, an all-women's institution, and found some possible factors contributing to the gender gap. The authors found that women who were older and had more wealth tended to have more financial knowledge. A different survey of the financial well-being of 368 women found that the women surveyed tended to be more conservative with their money, and women who were older and had more wealth tended to have better perceptions of their financial well-being (Malone, Stewart, Wilson, & Korsching, 2010). While the study did not examine financial literacy explicitly, it did provide a picture of what might possibly be contributing to the gender gap. Thus, American women appear to have less financial knowledge than men, and research has yet to determine why this is the case.

2.4.3 Gender Differences in Financial Decisions

Interestingly, the pervasive gender gap in knowledge does not always correlate to gender differences with respect to financial decisions. Some studies have reported gender differences (Lusardi & Mitchell, 2007; Lusardi & Mitchell 2008; OECD, 2013b), while others failed to find that a lack of financial knowledge influences gender differences in financial decisions (Ameriks et al., 2003; Atkinson & Messy, 2012; Robb & Sharpe, 2009). In addition to financial knowledge, Atkinson and Messy (2012) examined both financial behaviors and financial attitudes by gender. The authors found that differences in behaviors depended upon the country. For example, in Norway and Ireland women had a higher average behavior score by at least 10 percentage points, while in Albania and Armenia, men had a higher average behavior score by at least six percentage points. Finally, attitudes toward thinking about long-term finances were measured. Albania and Poland were the only countries where women tended to have longer-term preferences than men (Atkinson & Messy, 2012). In some studies, the authors found that women in developed countries tend to hold less wealth than men and tend to make different financial decisions than their male counterparts. Klapper and Panos (2011) split their 1,400-person sample into three groups of retirement planners: planners with private pensions, planners with public pensions, and nonplanners. The authors found that planners with private pensions tended to answer more questions correctly than those in the other two groups, and there was no difference between the planners with public pensions and the nonplanners (Klapper & Panos, 2011). Using a sample of 513 American adults, Ameriks et al. (2003) found that differences in attitudes toward money were related to wealth accumulation. Using regression analyses, the authors found that both the propensity to plan based on attitudes and financial skills as well financial planning were positively related to wealth accumulation. They found no differences between male and female respondents. Yet, depending on the sample, many have found no difference in financial behaviors such as wealth and financial planning (Ameriks et al., 2003; Atkinson & Messy, 2012) and credit card use (Robb & Sharpe, 2009). More research needs to be conducted regarding differences in financial decisions by gender before solid conclusions can be drawn.

2.5 Gender Gap at the High School Level

Interestingly, the gender gap in the financial knowledge of high school students is not as definitive. Some research points to a typical gender gap in which males outscore females (Becchetti et al., 2013; Lührmann et al., 2012; Varcoe et al., 2005), while some research found either no difference in financial knowledge by gender or found that female students exhibited slightly higher scores than their male counterparts (Hill & Asarta, 2016; Jang et al., 2014; Walstad et al., 2010).

2.5.1 Gender Gap at the High School Level Internationally

Internationally, some smaller scale studies have shown that the gender gap in financial knowledge favoring males does exist in countries such as Germany, Japan, New Zealand, and South Korea (Becchetti et al., 2013; Jang et al., 2014; Lührmann et al., 2012). In Germany, for example, female students were found to have less financial knowledge before taking a financial literacy course and were less likely to save their money than male students (Lührmann et al., 2012). In New Zealand, gender was initially a significant predictor of financial knowledge, but as more explanatory variables were added, it was no longer a predictive factor in determining high school financial knowledge (Cameron et al., 2014). In South Korea, the Korean Financial Literacy Test Survey (KFLTS) was administered to 1,185 high school students, and regression analyses showed no gender difference in scores (Sohn et al., 2012). Yet, another subsequent South Korean study used the *FFFL-HS* test and found that female high school students scored slightly higher than male students (Jang et al., 2014). More research is needed to determine whether or not there is a gender gap both within individual countries and among larger international samples.

2.5.2 Gender Gap in American High Schools

The differences in the financial knowledge of American adults by gender are likely correlated with the same gap among American high school students. However, studies into the financial knowledge gender gap among high school students reveal mixed results. In the United States, these mixed results seem to depend on which group of students was sampled and on the assessment given to those students. For example, using data from the Jump$tart survey given in all fifty states in 1997 and in 2000, Tennyson & Nguyen (2001) found no difference in the financial knowledge of male and female students. Mandell and Klein (2007) used data from the 1997 Jump$tart survey and also found no gender gap in financial education knowledge among high school students. Walstad et al. (2010) studied the effectiveness of the *Financing Your Future (FYF)* curriculum using data from four states and found no statistically significant difference in male and female test scores on both the pretest and the posttest. The authors, however, found that female students showed a statistically greater increase in their scores from pretest to posttest (Walstad et al. 2010). Most recently, Hill and Asarta (2016) assessed the effectiveness of the *Keys to Financial Success* high school personal finance program and found that females performed slightly better overall on the *FFFL-HS* test than their male counterparts. Taken together, these studies indicate that there is no gender gap in financial knowledge at the high school level in the United States.

Other studies, however, point to a very prominent gender gap in financial knowledge at the high school level in the United States. Varcoe et al. (2005) studied the effectiveness of the Money Talks curriculum and found that male students had more financial knowledge than their female peers. In terms of financial behaviors, more male students were found to have savings accounts than female students (Varcoe et al., 2005). Peng et al. (2007) used a survey of investment knowledge and found that male students not only showed more understanding of financial concepts but they also saved more money than their female peers. The most striking evidence indicating a prominent gender gap in personal finance achievement comes from a study that examined NLSY data. Lusardi et al., (2010) found that women were less likely to answer questions correctly, thus leading to a statistically significant difference in measures of financial knowledge. Though the findings are not necessarily generalizable, as only three financial knowledge questions were asked, the findings held under multiple data sample and multiple methodologies. Butters et al., (2012) found a prominent gender gap in the financial knowledge of high school students using the *FFFL-HS* Assessment through the National Finance Challenge. Determining whether or not a gender gap in the financial knowledge of high school students does exists requires further examination.

2.6 Factors Influencing Financial Literacy

Among many factors influencing financial literacy, a few appear frequently in the literature and are important in the context of the PISA 2012 Financial Literacy Assessment. These factors can also help to explain a gender gap in financial knowledge among high school students. First, parents have been shown to potentially influence their children's understanding of financial concepts through consumer socialization (Denhardt & Jeffress, 1971; Moschis, 1985; Ward, 1974). Parental characteristics, such as wealth and educational attainment, have also been shown to affect a child's financial knowledge (Jorgensen & Savla, 2010; Mandell & Klein, 2007; Tennyson & Nguyen, 2001). Also, a number of macroeconomic variables can have an effect on financial knowledge (Behrman et al., 2010; Jappelli, 2010; Jappelli & Padula, 2013).

2.6.1 Parental Influence

2.6.1.1 Consumer Socialization and Parents

Parents can affect how their children view financial matters. Children grow up learning from their parents how to be consumers and how to live in the economic world around them (Denhardt & Jeffress, 1971; Moschis, 1985; Ward, 1974). This process is known as consumer socialization, which is defined as "processes by which young people acquire skills, knowledge, and attitudes relevant to their functioning as consumers in the marketplace" (Ward, 1974, p. 2). Closely related is the idea of economic socialization, which is defined as learning about the economy and economics as a social process (Denhardt & Jeffress, 1971). Having a high level of financial knowledge and good financial behaviors fits well within the definition of consumer socialization. Within the context of consumer socialization, parental influence can have a large impact on the process. For example, Dotson and Hyatt (2005) conducted a factor analysis of survey data from students about what they felt influenced their consumer decisions. Students in this study reported that their parents had a strong influence on their own financial decisions. Unfortunately, Dotson and Hyatt (2005) did not delve further into what the parental influence looked like or the causal effect of parents. Parents can explicitly and implicitly teach their children how to be consumers (Jorgensen & Savla, 2010; Moschis, 1985; Ward, 1974). Parents can therefore transfer knowledge about being a consumer to their children. Danes (1994) surveyed 182 parents about the age at which parents should discuss financial matters with their children, and the consensus was that they should begin discussions around age 12. Discussing financial matters with children from a young age shows the importance that parents can have on their children's understanding of financial concepts. The importance of parental influence was also shown when examining college students' attitudes toward money and communication. A survey of 1,317 students revealed that girls tended to be more open and communicative with their parents regarding financial matters than boys were (Edwards, Allen, & Hayhoe, 2007). Research indicates that parents can have a profound effect on their children's understanding of consumer matters.

The process of consumer socialization differs by gender. Sons and daughters appear to learn differently from their parents or place differing emphasis on parental influence. More specifically, through a series of correlation analyses, Newcomb and Rabow (1999) found that sons perceived that their parents put more emphasis on earning money than daughters did. Jorgensen and Salva (2010) found that while there was no gender gap in financial knowledge, men and women placed different emphasis on parental influence in regards to financial matters. Structural equation modeling examining gender and perceived parental influence on financial knowledge showed that men who believed they learned about their finances implicitly from their parents scored higher than all others. Conversely, women who believed they had learned explicitly about finances from their parents had better financial behaviors (Jorgensen & Salva, 2010). Dotson and Hyatt (2005) found a similar result: girls in grades 4-11 thought that their parents had more influence on the girls' finances than their male peers. Edwards et al. (2007) found that male college students in Arkansas, Missouri, Louisiana, and Kentucky were less open with their parents about their finances than female students, indicating that the males did not value parental input in financial matters.

One study found no parental influence in regards to their children's financial knowledge and behaviors. In Italy, Becchetti et al., (2013) used DID models to test the effect of a financial education program for high school students. Results indicated that parents' occupations and educational attainment had no impact on the financial knowledge of their children. The study seems to be outnumbered, however, as most studies indicate some impact of parents on their children's understanding of financial matters.

2.6.1.2 Parental Influence on Financial Behaviors

Parent influence has been found to potentially influence financial behaviors in addition to financial knowledge. College students who reported their parents fighting about finances were found to have increased credit card debt; this was especially true for female students (Hancock et al., 2013). In a sample of 173 college students, step-wise regression results showed that students whose parents argued about financial matters had a 2.8 times higher chance of carrying a credit card balance and a 2.1 times higher chance of having two or more credit cards (Hancock et al., 2013). Norvilitis and MacLean (2010) found that college students' credit card debt decreased with increased parental mentoring of credit card debt. Also, Grinstein-Weiss, Spader, Yeong, Taylor, and Freeze (2011) found that adults who had learned money management skills from their parents had higher credit scores and lower amounts of credit card debt. Huang, Nam, and Sherraden (2013) found that mothers in Oklahoma who opened college savings accounts for their children were more likely to have increased financial knowledge. While there was no statistical measure of the influence these mothers had on their children’s personal finance knowledge or behaviors later in life, the mothers’ influence likely could lead to their children achieving increased personal finance knowledge, something the program in Oklahoma was hoping to accomplish. Together, these studies have shown the influence that parents can have on their children’s subsequent financial behaviors.

2.6.1.3 Parents and Financial Knowledge

Outside of direct influences on financial knowledge, many studies focused on parents’ influence on the financial knowledge of their children rather than using direct measures of the parents’ financial knowledge. For example, parent income was positively correlated with financial knowledge and financial behaviors of teenagers. The College Student Financial Literacy Survey (CSFLS) indicated that the higher a family’s income, the higher the student’s score on a test of financial knowledge (Jorgensen & Savla, 2010). Also, students whose parents were college graduates were more likely to be financially literate and have better attitudes towards financial issues (Mandell & Klein, 2007). Overall, the higher a parent’s educational attainment, the higher a student’s score on a financial knowledge test (Tennyson & Nguyen, 2001). However, one study from the Netherlands found the opposite. van Rooij et al. (2012) found that students whose parents had low levels of financial literacy actually had a greater understanding of financial concepts because they were motivated to learn about the financial matters their parents did not understand.

Not all studies reported positive relationships between parental characteristics and their children’s personal finance knowledge. For example, the parent’s gender may have no influence on the child’s personal finance knowledge (Jorgensen & Savla, 2010). Another study found that there was no correlation between students’ financial knowledge scores and the financial knowledge scores of their parents on the same 19-question assessment (Bowen, 2002). Yet, the results from Bowen (2002) are not generalizable, as the number of students in the study was only 64 and the number of parents was 47. With respect to financial behaviors, a survey of alumni from a Midwestern university indicated that increased savings rates among parents actually had a negative effect on savings rates among their children (Peng et al., 2007).

2.6.2 Country-Level Variables

Just as financial literacy can have individual effects on financial decisions and outcomes, it can also have effects on the economy as a whole (Widdowson & Hailwood, 2007). The literature regarding the relationship between macroeconomic variables and financial literacy is not extensive, but some macroeconomic variables do arise as being potentially related to financial literacy. The first variable that could be related is gross domestic product (GDP). One international study found that GDP per capita was not related to economic and financial literacy (Jappelli, 2010). Jappelli (2010) examined different summary indicators of economic literacy from the IMD World Competitiveness Yearbook (WCY) from 1995 to 2008. When examining economic literacy through regression analysis, Jappelli (2010) found that PISA math scores were positively correlated with the indicator of economic literacy, but GDP was not. Expanding that finding, Jappelli and Padula (2013) discovered that GDP growth also was not related to financial literacy. The finding came from an analysis of Survey of Health, Ageing, Retirement in Europe (SHARE) data, which is a representative sample of European individuals over 50 years old. Using an intertemporal consumption model of investment in financial literacy, the authors found that GDP has no impact on the choice to consume financial literacy. The relationship between GDP and financial literacy could benefit from further investigation. Income inequality was also found to be related to financial literacy. More specifically, countries with less income inequality tended to have higher average levels of economic/financial literacy; much of the analysis was completed using Gini coefficients (Lo Prete, 2013). The finding regarding income inequality holds true for over 30 countries included in the IMD WCY. Finally, the unemployment rate was hypothesized to be related to financial literacy in Chile, but no relationship could be statistically determined through the use of instrumental variables regressions (Behrman et al., 2010). In an international assessment of financial knowledge, it would be valuable to explore whether financial knowledge is related to macroeconomic variables such as GDP and the unemployment rate.

Chapter 3

BACKGROUND AND DATA

This chapter provides background information on the dataset used to examine the financial knowledge of a sample of high school students from around the world. Section 3.1 discusses the data, the PISA 2012 Financial Literacy Assessment. Section 3.2 discusses the country sample, the school sample, and the student sample used to create the hierarchical dataset. Section 3.3 contains information about the questionnaires that were part of the assessment. Finally, Section 3.4 describes the Financial Literacy Assessment and scoring issues.

3.1 Data

The Programme for International Student Assessment, or PISA, is an international assessment of students' skills and knowledge conducted near the end of their compulsory education. By assessing mathematics, reading, science, problem solving, and financial literacy, the PISA Assessment examines not only literacy in certain content areas, but it also offers key insights into different educational policies and practices around the world. In 2012, the Organisation for Economic Co-operation and Development (OECD) administered a variety of PISA Assessments to around 500,000 15-year-old students in 65 countries. The Assessment of Financial Literacy was included in the 2012 PISA, the first large-scale assessment of financial literacy administered worldwide to high school-aged students. A total of 18 countries participated in the paper-based PISA Financial Literacy Assessment. By including the new financial literacy section in the 2012 PISA, the OECD hoped to not only test the financial capabilities of students across the developed world, but also aid countries in putting in place the best possible policies for increasing the financial literacy of their citizens.

3.2 Sample

3.2.1 Country Sample

Since the Financial Literacy Assessment was new in 2012, countries were not required to administer the assessment as part of their overall PISA testing. As a result, students from only 18 countries took the Financial Literacy Assessment. Of these 18 countries, 13 are members of the OECD. The OECD countries and economies that administered the assessment were Australia, the Flemish Community of Belgium, the Czech Republic, Estonia, France, Israel, Italy, New Zealand, Poland, the Slovak Republic, Slovenia, Spain, and the United States. In addition to the OECD members, five non-member countries partnered with the OECD for the purpose of administering the PISA Financial Literacy Assessment. These partner countries were Colombia, Croatia, Latvia, the Russian Federation, and the economy of Shanghai-China (OECD, 2014a).

3.2.2 School Sample

International studies like PISA strive to create comparability across national target populations. Due to vast differences in educational systems across the world, PISA used age to target populations within countries instead of grade levels. The OECD targeted and sampled students between 15 years and three months of age, and 16 years and two months of age for the PISA Assessment. A two-stage stratified sampling method was used, where schools within countries were sampled first. Schools where 15-year-old students could be enrolled were chosen based on probabilities proportional to the number of 15-year-old students within their schools. Therefore, schools with a greater number of 15-year-old students had a higher chance of being selected. To obtain a representative sample, each country was required to select a minimum of 150 schools. If a school was chosen to administer the PISA 2012 examination, they could self-select out of the assessment and a replacement school was then selected.

3.2.3 Student Sample

Once schools were selected, a subsample of students from within each school was chosen to take the assessment as part of the second step in the two-stage stratified sampling procedure. Lists of all students fitting the age range were collected from each selected school. For the general PISA 2012 Assessment, 35 students were randomly selected in each school. For countries that chose to administer the optional Financial Literacy Assessment, schools randomly selected at least 43 students; 35 students took the core assessment (reading, math, science, problem solving), and eight students from each school completed the Financial Literacy Assessment. In all, 29,041 students completed the assessment in financial literacy. This sample is representative of approximately 9 million 15-year old students from the 18 participating countries (OECD, 2013a, 2014a).

3.3 Measures

3.3.1 Student Questionnaire

As part of the PISA Assessment, students were required to complete a demographic questionnaire. All students were required to answer questions about themselves as well as provide information about their families and their home lives. The student questionnaire used a rotated design to cover more aspects of a student's life without lengthening the time it took to administer the assessment. Depending on which assessment booklet students were given, they may have been asked to complete different sections of the questionnaire.

In addition, all students who were given the Financial Literacy Assessment completed a short money management questionnaire at the end of the assessment. This questionnaire included questions about non-cognitive aspects of financial literacy such as if the student had a bank account and/or if the student discussed financial matters with their family. All data collected from both student questionnaires was coded and compiled into a dataset with 615 student-level variables.

3.3.2 School Questionnaire

Principals or other school administrators from each school were asked to complete a school questionnaire. In addition to basic information about the school's makeup, location, and culture, principals were asked questions about financial education in their schools. Specifically, they were asked questions about whether financial education was offered, and if so, whether financial education was mandatory, and how much financial education was provided in their schools in the event that it was offered. Two hundred ninety-one school-level variables are available.

3.3.3 Country Measures

Individual countries were not asked to provide information for PISA. Instead, individual participants were asked to provide information regarding their country of origin and in which region of the country they currently resided. School administrators were also asked to provide information on the region of the country in which their school was located. In order to extend the analysis further, I obtained additional variables at the country level from the World Bank and merged them with the PISA data. These measures include real GDP per capita, unemployment rates for the overall population, and separate labor force participation rates for men and women. These measures are used to predict financial literacy at the country level.

3.3.4 Datasets

Datasets for assessment results, student demographic information, parent demographic information, and school information are publicly available from the OECD. The separate datasets can be linked through the use of student id numbers. The resulting cross-sectional dataset contains variables at the individual and school level as well as variables indicating the country and state or region in which the school can be found. The dataset is nested: students nested within schools, nested within countries. Sample sizes for each country are presented in Table 3.1.

Table 3.1 Sample Sizes for Schools and Students within Countries, PISA 2012

Country/Economy (N=18)	Number of participating schools	Number of participating students
OECD Member Countries/Economies		
Australia	768	3,293
Flemish Community (Belgium)	161	1,093
Czech Republic	288	1,207
Estonia	200	1,088
France	225	1,068
Israel	153	1,006
Italy	1,158	7,068
New Zealand	176	957
Poland	177	1,054
Slovak Republic	224	1,055
Slovenia	307	1,312
Spain	179	1,108
United States	158	1,133
Non-OECD Member Countries/Economies		
Colombia	346	2,100
Croatia	163	1,145
Latvia	203	970
Russian Federation	219	1,187
Shanghai-China	155	1,197
Total	5,260	29,041

3.4 Assessment

The financial literacy portion of the PISA Assessment was given as a paper-based test over a two-hour time frame. Students were given four 30-minute clusters of questions in three different content areas: reading, mathematics, and financial literacy (two clusters). The Financial Literacy Assessment was administered in four different randomly assigned test booklets. Each booklet contained two financial literacy clusters as well as one math cluster and one reading cluster. For students with special needs, there was a test booklet containing just one financial literacy cluster and one math cluster. Students also completed a short, five-minute questionnaire about their attitudes toward money after they completed the assessment. This questionnaire was only given to students who completed the Financial Literacy Assessment.

Each financial literacy cluster consisted of 40 questions, some of which were multiple-choice and some of which were constructed response. Questions covered the following four content areas: money and transactions; planning and managing finances; risk and reward; and financial landscape. These content areas were selected based on the OECD's reviews of content contained in the financial literacy frameworks already in use in many countries around the world (OECD, 2014a). The money and transactions domain included questions regarding the awareness and usage of money and other forms of payment in daily life. Planning and managing finances contained questions about both short-term budgeting and long-term effects of money management. The risk and reward area was concerned with how well students understood how to balance financial risks while recognizing the potential for both gains and losses. Finally, the financial landscape domain was concerned with whether students understood the role that consumers play in the financial marketplace as well as identifying the effects of changes in economic and financial conditions (OECD, 2014a).

In addition, four process categories were used to test how well a student could apply concepts within personal finance and problem solve certain situations pertaining to each domain. These processes included: identifying financial information; analyzing information in a financial context; evaluating financial issues; and applying financial knowledge and understanding. Identifying financial information included tasks such as looking at contracts, forms, and invoices, and answering questions based on these tasks. When students were asked to analyze information in a financial context, among other things, they were asked to compare/contrast or synthesize implications of financial decisions such as choosing a good cell phone contract. The evaluating financial issues questions asked students to use critical thinking skills to analyze a finance-related problem such as deciding what to purchase in a store given a limited budget. The process of applying financial knowledge and understanding asked students to solve problems using mathematical calculations.

Given that financial literacy was to be tested in real life situations, four context categories were tested. The goal was to place questions in contexts that 15-year-old students around the world would be able to understand and interpret. These contexts included education and work; home and family; individual; and societal. While the exam questions have not been released, information about the subject, context, and process tested in each question is available within the dataset (OECD, 2013a, 2014a).[2] Detailed information about all of the assessment questions' content, processes, and contexts can be found in Appendix C.

Some patterns by question type appear in the data. In terms of content area, students performed best in the categories of planning and risk and reward, achieving an average score of 60.71% and 60.84% correct, respectively. The most challenging content for student was in the landscape category, where students, on average, answered only 31.95% of the questions correctly. Students in the PISA Assessment performed best on questions about the evaluating financial issues process (63.3%

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[2] Appendix B contains sample questions, with relevant supporting information.

correct), and students performed worst on questions regarding the identifying financial information process (47.53% correct). Students were best able to correctly answer questions put in a societal context (64% correct), while they were least able to correctly answer questions put in the context of education and work (48.77% correct).

3.4.1 Scoring

Since the PISA Assessment aimed to measure student literacy with a proficiency measure, student scores are not simply the sum of the questions answered correctly. To best account for international differences, not all students were given the same test booklets or same questions to answer. This structure further complicates the scoring mechanism. Therefore, student "scores" are reported as plausible value (PV) data rather than as individual scores. Student proficiencies are not directly observed, and therefore they must be inferred from the available observed data (OECD, 2014a). According to the OCED (2014a), "PVs are a selection of likely proficiencies for students that attained each score" (p. 146). These PVs are good measures for examining the overall performance of a population of students.

Raw data from the PISA Assessments was scored for correctness. Multiple-choice questions were given either full credit or no credit. Constructed-response questions were assigned full credit, partial credit, or no credit depending on the question asked. In order to successfully transform the raw data into PVs useful for analysis, steps were taken by the OECD to correctly transform and weight overall scores from the cognitive data in order to make comparisons within and across countries. After the data was transformed, a Rasch model and a mixed coefficients model were used to analyze the test items. Plausible value intervals, or ranges of likely estimates of student proficiencies, and weighted likelihood estimates were used to construct exam "scores," rather than raw scores, as these better fit the international population represented in the PISA 2012 dataset (OECD, 2014b).

In addition, OECD statisticians performed national calibrations on unweighted data to decide on test items and item fit in each country. National calibrations were done in order to account for differences in test booklets and questions within countries. As necessary, items were deleted using item response model fit statistics and discrimination coefficients. Then, national reports were presented in order to make comparisons across countries. Finally, international calibrations were conducted to account for differences in test booklets both within and among individual countries (OECD, 2014b). Given the sampling strategy and the complex nature of international data, these steps were necessary to ensure that results could be compared across countries and to correct for sample differences.

After examining test item fit and weighting scores, student scores were generated using conditioning variables and appropriate weights. Since 2012 marked the first administration of the financial literacy portion of the exam, all that was necessary to transform the plausible value data, or likely proficiencies data, into scaled scores was to standardize scores to a mean of 500 with a standard deviation of 100 (OECD, 2014b). In addition, the reading and mathematics items that were administered with the Financial Literacy Assessment were standardized separately according to the same parameters.[3] After these steps were taken, the overall financial literacy exam scores are then comparable across countries.

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[3] It should be noted that the reading and mathematics items that were part of the financial literacy assessment cannot be directly compared to the standard PISA reading and mathematics items, as the content and sample sizes were different.

3.4.2 Proficiency Levels

In addition to generating student-scaled scores, the OECD and experts in specific content areas generated proficiency levels in order to delineate what typical students of differing ability levels should hypothetically know and make comparisons across countries. The PISA Assessment was designed so that item response modeling could be used to estimate not only student ability but also the difficulty of individual test items (OECD, 2014b). This design, in turn, enabled ability levels to be linked with specific assessment questions and proficiency levels to be created.

Proficiency levels were developed by a number of experts in the appropriate fields who identified potential scales, assigned items to the scales, adjusted the scales before field testing, used field testing data to further refine the scales, and revised the scales.[4] These scales allow for a probabilistic relationship between student ability and item difficulty, meaning that students with higher abilities have a higher probability of getting the more difficult questions correct and vice versa (OECD, 2014b). Five proficiency levels were created for the Financial Literacy Assessment. Figure 3.1 provides a summary of these levels.

[4] More information can be found in the PISA 2012 Technical Report – OECD (2014b).

Level	Score Range	Percentage of students able to perform tasks at each level or above	What students can typically do
1	326 to less than 400 points	95.2%	• Can identify common financial products and terms • Can recognize difference between needs & wants • Make simple decisions on everyday spending • Recognizes purpose of everyday financial documents (i.e. invoice) • Can do simple math within this context
2 (Baseline)	400 to less than 475 points	84.7%	• Can apply knowledge of common financial products and terms • Can use information to make financial decisions in relevant contexts • Recognizes value of simple budget and can interpret prominent features of financial documents • Applies basic numerical operations to answer financial question • Shows understanding of relationships between different financial elements
3	475 points to less than 550 points	61.8%	• Can apply knowledge of common financial products and terms relevant to them • Considers consequences of financial decisions • Can make simple financial plans • Interpret sand evaluates range of financial document • Applies a range of basic numerical operations, including calculating percentages • Chooses correct numerical operations to solve financial literacy context questions
4	550 to less than 625 points	31.6%	• Applies knowledge of less common financial concepts and terms that will be relevant in adulthood • Interprets and evaluates range of detailed financial documents • Explains functions of less commonly used financial products • Makes financial decisions taking into account longer-term consequences • Solves routine problems in less common financial contexts
5	Equal to or higher than 625 points	9.7%	• Applies understanding of wide range of financial terms and concepts to contexts that may only be relevant much later in life • Analyzes complex financial products and features of financial documents • Works at high level of accuracy solving non-routine financial problems • Describes potential outcomes of financial decisions • Shows an understanding of a wider financial landscape

Figure 3.1 Summary Description of the Five Levels of Proficiency in Financial Literacy

Note: Adapted from Organisation for Economic Co-operation and Development. (2014a).

The five scales represent different ability levels for the Financial Literacy Assessment. Each level contains a range of 75 points. Over 95% of students across the 18 countries performed at Level 1 or higher. Level 2 is considered to be the financial literacy baseline, or about what most students should be able to achieve given differing item difficulties on the assessment. Overall, 84.7% of students were able to perform at least at the baseline level. Close to 62% of students were able to perform at or above Level 3, and 31.6% of students performed at or above Level 4. At Level 5, students should be able to answer the most difficult questions and are considered the highest performers. In the sample, only 9.7% of students performed at Level 5 (OECD, 2014a). Since ability is not directly measured, these scales provide a way to estimate ability levels in financial literacy, especially at low and high levels of achievement.

Chapter 4

DO GENDER AND PARENTAL CHARACTERISTICS INFLUENCE FINANCIAL KNOWLEDGE?

This chapter examines the relationship between gender and financial knowledge, as well as the relationships between parental characteristics and student financial knowledge. This chapter focuses on providing the answer to the following research questions posed in Section 1.2.1 of this dissertation:

1. How does financial knowledge vary by gender in students around the world?

2. Are parental characteristics related to a student's understanding of financial matters? How are parental characteristics related to gender differences in financial knowledge?

4.1 Introduction

To be a successful citizen in today's world, individuals must grasp concepts related to money and other financial matters; thus, citizens must possess a certain amount of financial literacy. The term financial literacy suggests that consumers have a basic understanding of how to use and manage money, as well as how to make use of this knowledge in the financial system they inhabit (Atkinson et al., 2007; Huston, 2010). According to the President's Advisory Council on Financial Literacy (PACFL),[5] financial literacy encompasses financial knowledge, financial skills,

[5] The name of this group has since been changed to the President's Advisory Council on Financial Capability.

perceived knowledge, and financial behavior in an interconnected series of relationships (as cited in Hung et al., 2009). Therefore, the term financial literacy is used to describe the understanding of personal finance and corresponding financial behaviors, while financial knowledge will refer only to the understanding of personal financial matters and not corresponding financial behaviors.

Using the PISA 2012 Financial Literacy Assessment, this chapter first examines student financial knowledge and whether or not a gender gap in financial knowledge is present. To clarify, analyses examine the financial knowledge of high school students rather than financial literacy, as the Financial Literacy Assessment measured knowledge and did not contain information regarding financial behaviors. Through the use of hierarchical linear modeling (HLM), or multilevel modeling, I examine financial knowledge across the sample of students within schools and within countries in order to best assess the nested nature of the data and to account for unequal variances. The multilevel modeling approach also allows for an examination of variance within students and within schools. Using this methodology, analyses focus on the correlations between parental characteristics and student financial knowledge, as well as whether or not any of these characteristics vary randomly at the school level. Building upon consumer socialization theory, it is determined whether or not parental characteristics have a significant relationship with student financial knowledge overall and whether or not significant relationships exist between gender and parental characteristics. This chapter adds to the growing body of literature examining the financial knowledge of high school students and the gender gap in financial knowledge by identifying potential factors that are associated with that gap.

4.2 Methodology

4.2.1 Multilevel Modeling

One increasingly popular estimation method in educational research is multilevel modeling, or hierarchical linear modeling (HLM). Multilevel modeling is particularly beneficial for data with nested structures, whereby random effects can be added to address the nested structure of the data and unequal variance. Nested data is by definition any data where individual observations exist within different organizational structures. In education, the structure tends to be students “existing” within classrooms, within schools, and/or within school districts (Osborne, 2000). Because of this structure, students within classrooms, for example, might share certain characteristics rather than being independent of their peers. Multilevel models are not far removed from ordinary least squares (OLS) estimation except that multilevel models account for the hierarchical nature of the data and the shared variance across observations (Woltman, Feldstain, MacKay, & Rocchi, 2012). Multilevel models, or HLMs, can include both fixed effects and random effects to allow for shrunken and more precise estimates as well as differing results among the different levels of analysis (Clarke, Crawford, Steele, & Vignoles, 2010). Multilevel modeling uses Bayesian estimation to produce an estimate that is a combination of prior information and the likelihood of the data. As a result, the estimation procedure creates “shrinkage” estimates, which is an estimate of a mean that is influenced by other groups in the data (Clarke et al., 2010; Gujarati & Porter, 2009).

Typically, when estimating which factors explain a dependent variable, the standard method of estimation used is ordinary least squares (OLS) or the classic linear regression model (CLRM). Using this estimation method, observations are fitted to a linear model that seeks to minimize the squared error between the observation and the estimated data point (Greene, 2012; Gujarati & Porter, 2009). Classic linear regression modeling has worked quite well across a variety of economic and educational applications, most often with fixed effects in the context of both cross-sectional and panel data (Clarke et al., 2010). With nested data, however, OLS and/or CLRM do not seem to be entirely appropriate.

Unlike OLS estimation, multilevel models estimate parameters as weighted averages of both the group mean and the overall mean. At a basic level, multilevel models cluster data using maximum likelihood estimates, which borrow strength from other data points and from other clusters/groups (Raudenbush & Bryk, 2002). Thus, multilevel models can explore links between the different levels, rather than just exploring the entire sample while controlling for a specific level (Michaelowa, 2001). Multilevel models are similar to linear regression except that an analysis of variance (ANOVA) term for the clusters is added (Raudenbush & Bryk, 2002). Thus, each cluster or group has its own intercept and slope terms, rather than just one intercept and slope term for the entire dataset. Here, the slope terms, or regression parameters, are known as fixed effects. Because a dataset is nested in nature, the residual term becomes more complex; there are residuals at every level of the data. These residuals at each level are known as random effects, and they can be estimated along with the fixed effects. Given the research questions as well as the nested structure of the PISA data, multilevel modeling is an appropriate methodology to use here.

Nested data or hierarchical data violates two of the main assumptions underlying the CLRM model and the OLS estimation process. Ordinary least squares modeling requires the data to be homoscedastic, or have equal variance. In other words, the error term needs to be the same for each observation. With nested data, error terms commonly have multiple components, one for each level or cluster (Moulton, 1986). Furthermore, the data will be dependent within clusters, thus causing heteroscedasticity, or unequal variance (Greene, 2012; Gujarati & Porter, 2009). When using nested data and not accounting for the nested structure of the data, estimates will exhibit smaller standard errors (Ammermüller, Heijke, & Wößmann, 2005). While other solutions to the heteroscedasticity problem and smaller standard errors exist within an OLS framework, the analyses in this chapter will justify the use of multilevel modeling to account for such issues.

The second issue that arises within the PISA dataset is that sample sizes vary across schools as well as across countries. Because there were different probabilities in schools and students being chosen in the sampled countries, this could have created overrepresentation of certain individuals in the sample (Deaton, 1997). To ensure that this was not the case in subsequent analyses, the OCED included sample weights for students and schools (OECD, 2014a, 2014b). For the purpose of my analyses, sample weights at the student level are used to ensure that analyses are representative of the target population of 15-year-olds in the sampled countries.

4.2.2 Educational Production Function

Standard microeconomic theory on production states that the level of output depends on a number of inputs, mainly labor and capital (i.e. tools and machines) (Nicholson & Snyder, 2012). The idea of transforming inputs into output has been applied to education to create an educational production function. Hanushek (1979) first used the term and showed that school inputs have an influence on educational achievement. Using a combination of individual student characteristics, teacher characteristics, and school characteristics, Hanushek (1986) subsequently showed that higher achievement levels were linked to better schools and better teachers. The functional form of the production function, however, was never fully defined. In fact, to date, there is no specific functional form for educational production functions (Krueger, 1999). The output can either be defined as achievement on standardized tests or, in more recent literature, as educational attainment levels. While functional forms may vary, the efficacy of the model has stood the test of time, with evidence that inputs at both the individual and the school levels have influenced student achievement (Hanushek, 1986; Hanushek, 1997; Hedges, 1994; Krueger, 1999; Rothstein, 2010).

Each model estimated takes the form of an educational production function modeling financial knowledge from the PISA 2012 Financial Literacy Assessment. Instead of the standard linear educational production function, the equations take the form specified by Raudenbush and Bryk (2002) in a multilevel modeling framework. The level-1 equation, or the student-level equation, takes the following form:

$$Y_{ijk} = \pi_{0jk} + \pi_{1jk}(X_{ijk}) + \varepsilon_{ijk} \quad (1)$$

where Y_{ijk} is a measure of financial knowledge for student i in school j in country k.

π_{0jk} is the intercept for school j in country k.

X_{ijk} is a vector of independent variables at the student level.

π_{1jk} are the student-level fixed effects.

ε_{ijk} is the student-level random effect (or variance).

To model the school effect,[6] the regression coefficients from the student-level equations are used as outcome variables. The level-2 general equations, or the school-level equations, take the following forms:

$$\pi_{0jk} = \beta_{00k} + r_{0jk} \quad (2)$$

$$\pi_{1jk} = \beta_{10k} + r_{1jk} \quad (3)$$

where π_{0jk} is the intercept for school *j* in country *k.*

π_{1jk} is the slope for school *j* in country *k.*

β_{00k} is the overall mean intercept for school j in country k.

β_{10k} is the overall mean slope for school j in country k.

r_{0jk} - r_{1jk} are the school-level random effects (or variance).

Finally, to model country effects,[7] the regression coefficients from the school-level equations are used as outcome variables. The level-3 equations, or the country-level equations take the following forms:

$$\beta_{00k} = \gamma_{000} + u_{00k} \quad (4)$$

$$\beta_{10k} = \gamma_{100} + u_{10k} \quad (5)$$

where γ_{000} is the average country intercept.

γ_{100} is the average country slope.

u_{00k} – u_{10k} represent the country-level random effects.

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[6] Here, “school effect” refers to the effect of a student being in a particular school. No causation is implied; it is simply the terminology used in this instance.

[7] As with school effects, the term “country effects” does not imply causation. It is the commonly used term to determine the effect of having a student be from a certain country.

4.2.3 Analyses

As the PISA 2012 data is nested in nature, three-level multilevel models are estimated to examine differences across students within different schools and within different countries. This approach allows for the determination of variance at the student level, at the school level, and at the country level while still answering questions about the relationships between gender, parental characteristics, and financial knowledge. For each model, an educational production function, with PVs as the dependent variable measuring student knowledge, is used to examine what role student and parental characteristics had on financial knowledge.

Previous research on international comparisons of student knowledge emphasized the importance of controlling for socioeconomic status (SES) and the opportunity to learn (OTL) (Schmidt, Cogan, & Houang, 2011), as these two variables can help to account for differences among students within different schools and within different countries. Thus, to first examine student performance, a measure of SES and a separate measure of OTL are used as grand-mean centered predictors of student performance (Model 1). To examine how gender is associated with financial knowledge, the self-reported gender of the student is added as grand-mean centered (Model 2). Parental characteristics are also examined (Model 3), and finally, interactions between parental characteristics and gender are examined (Model 4) to explore how they are associated with student financial knowledge.

The type of multilevel models used in these analyses is known as random coefficient modeling. Combining fixed effects and random effects, random coefficient models estimate a dependent variable at level 1 (the student level of analysis) while building and averaging separate regression models for each higher-level group (schools and countries). Here, fixed effects results are analyzed as well as the random intercepts and the random slope on the gender variable. For the purpose of these results, fixed effects are analogous to ordinary least squares regression coefficients, while random effects are analogous to error terms with one major difference. Essentially, the fixed effects estimates produced are averages of the fixed effects at the student level and random effects at the higher levels of analysis (Garson, 2013; Raudenbush & Bryk, 2002). In this chapter, the research questions seek to determine what is occurring in terms of student knowledge across the sample of schools and countries, not within specific schools or specific countries. Thus, random effects are discussed in terms of significance only and estimates of random effects are not further analyzed. Three-level multilevel models have multiple error terms, one for the student level and many for the school level, or there were multiple random effects. This allows for the separation of the variance in the outcome into three levels, student-level variance, school-level variance, and country-level variance. In this chapter, analyses also make use of random effects of student-level predictors to determine if these predictors varied at the school level. This is done in order to examine variance at the school-level, as well as to justify the use of multilevel modeling.

4.2.4 Estimation Technique

Analyses are conducted in SAS® 9.2 statistical software using the PROC MIXED procedure for multilevel models. Since the PISA 2012 dataset contains a range of scores for each student, or PVs, analyses needed to account for five different dependent variables. Following advice from the OECD and statisticians at SAS®, analyses are run for each PV and then averaged to obtain the most accurate results across the range of PVs for student achievement (OECD, 2009). Since the sample is relatively large, the five estimates for student achievement as well as the standard errors are quite close, but the analyses are still run and averaged to ensure the most accurate and robust results. Models are estimated using the default options of restricted maximum likelihood estimation (REML), the basis for estimation in mixed or hierarchical modeling. To control for the degrees of freedom for unequal variances in the data, the Satterthwaite method is used, as this method is best suited for the unbalanced design of students within schools and the complex covariance structures (Bell, Ene, Smiley, & Schoeneberger, 2013).

To test the model specifications, diagnostics measures are examined to determine if any observations exhibited any influence over the results and if the residuals are normally distributed. Heteroscedasticity did not need to be checked, as multilevel modeling already accounted for such a problem. For all of the models estimated, the student residuals appear to be normally distributed and thus do not require further examination. Influence statistics for each model present a different story. Quite a few observations exhibit high influence and warrant further examination. When examining the observations that could influence the fixed effects results, dropping them from the model did not change the fixed effects estimates. There were some slight changes to the covariance parameters (or the random effects); however, since my research questions are only concerned with whether or not the random effects are statistically significant, I decided to keep all observations in the model.

As with most international studies, weights are utilized to account for the differences in sample sizes within schools as well as to account for differing sampling variances within schools. The PISA 2012 Financial Literacy Assessment data has a total of 81 weights at the student level, which includes both the final weight and replicate weights. Replicate samples are formed through transformations of the actual sample, and this transformation included obtaining replicate weights for each of the replicate samples. For the purpose of answering these research questions, the finalized student-level weight is used in the final analyses, as was advised by statisticians from the OECD working on PISA 2012 data. Furthermore, when running analyses using each of the 81 replicate weights, results were very similar. Only the student-level finalized weight is used to account for different sample sizes in the number of students across schools and countries, though a school-level weight does exist. The reason that only the student-level weight is used is because SAS® 9.2 only allows for the use of a root-level weight (in this case, the student-level weight) (Uekawa, 2004).

4.3 Results

4.3.1 Descriptive Statistics

A total of 29,041 students from 5,260 schools in 18 countries were administered the PISA 2012 Financial Literacy Assessment. Given the rotated design and subsequent analyses in this study, the sample size is smaller than the original sample. The main reason for the smaller sample size is due to missing student reported data. Students were asked to complete an additional, two-page money management survey as part of the overall assessment. Unfortunately, students were only asked to complete either the first page or the second page, which caused the original sample size to be cut in half. The remaining observations are examined for completeness, and any individual observations with missing data for parental characteristics are dropped from subsequent analyses.

The final restricted sample makes use of data from 9,929 students from 3,964 schools in 18 countries. This sample will henceforth be referred to as the restricted sample. Table 4.1 presents sample sizes for both schools and students within each country.

Table 4.1 Sample Sizes for Schools and Students within Countries, Restricted Sample, PISA 2012

Country (N=18)	Number of participating schools	Number of participating students
OECD Member Countries/Economies		
Australia	148	248
Flemish Community (Belgium)	29	53
Czech Republic	282	541
Estonia	204	432
France	229	433
Israel	30	54
Italy	1,061	3,149
New Zealand	148	344
Poland	181	449
Slovak Republic	184	431
Slovenia	256	558
Spain	188	441
United States	153	462
Non-OECD Member Countries/Economies		
Colombia	176	431
Croatia	190	517
Latvia	162	382
Russian Federation	167	398
Shanghai-China	176	606
Total	3,964	9,929

The sample sizes vary greatly across countries. For example, Italy has the largest number of participating schools at 1,061, whereas the Flemish Community of Belgium has the smallest school sample at 29 participating schools. Student samples range from 53 students in the Flemish Community of Belgium to 3,149 students in Italy. As previously mentioned, to prevent larger sample sizes in specific countries from affecting the results, the student-level finalized weight is used in all subsequent analyses.

For the purpose of this chapter, parental characteristics reported by students are examined to determine their correlation with student performance. All of the variables of interest are at the student level of analysis and are self-reported by students. Variables used in subsequent analyses include the gender of the student (*Male)*; the mother's highest level of schooling (*Mother's Highest Schooling)*; the mother's employment status (*Mother Employment)*; the father's highest level of schooling (*Father's Highest Schooling)*; the father's employment status (*Father Employment)*; whether the student's mother lives in the student's household (*Mother Lives in Home)*; whether the student's father lives in the student's household (*Father Lives in Home)*; how often the student discusses money matters with their parents or other adults (*Talk about Money*); and whether or not students learned to manage money in school (*Learn about Money in School*). Both *Mother's Highest Schooling* and *Father's Highest Schooling* are categorized using International Standard Classification of Education (ISCED) levels. Students were asked to report the highest level of their parents' schooling ranging from the equivalent of no primary education to upper secondary education with the intention of going to post-secondary education. International Standard Classification of Education levels were used to account for differences in educational systems around the world.[8] Both *Mother's Highest Schooling* and *Father's*

[8] A conscious choice was made to not create dummy variables for each level of education presented. The purpose of including both the mother's and father's highest levels of education was to determine whether or not more educated parents were

Highest Schooling are only reported to the level of high school graduation, or its equivalency. *Talk about Money* represents a categorical variable as to how often students talked about money with their parents or other adults, ranging from never or hardly ever to almost every day. With the exception of the variables for *Mother Lives in Home* and *Father Lives in Home,* all parental variables are entered into the model as uncentered. Both *Mother Lives in Home* and *Father Lives in Home* were entered into the model as group-mean centered. The *Learn about Money in School* variable was included to measure the students' opportunity to learn (OTL) about financial matters. Table 4.2 contains information about means, standard deviations, sample sizes, and variable explanations for each independent variable of interest.

Table 4.2 Sample Means, Restricted Sample, Parent Analyses, PISA 2012

Variable	Mean	Explanation
Male	0.50 (0.50)	0 = Female 1 = Male
Mother's Highest Level of Schooling (Mother's Highest Schooling)	4.31 (0.92)	1 = Did not complete ISCED level 1 2 = ISCED, level 1 3 = ISCED, level 2 4 = ISCED, level 3B, 3C 5 = ISCED, level 3A

associated with children with more financial knowledge. The goal was not to determine whether or not specific educational credentials were associated with student financial knowledge.

Table 4.2 continued

Mother's Employment Status (Mother Employment)	0.72 (0.45)	0 = not employed 1= employed
Father's Highest Level of Schooling (Father's Highest Schooling)	4.23 (0.96)	1 = Did not complete ISCED level 1 2 = ISCED, level 1 3 = ISCED, level 2 4 = ISCED, level 3B, 3C 5 = ISCED, level 3A
Father's Employment Status (Father Employment)	0.89 (0.31)	0 = not employed 1= employed
Mother Lives in Student's Household (Mother Lives in Home)	0.96 (0.18)	0 = No 1 = Yes
Father Lives in Student's Household (Father Lives in Home)	0.88 (0.32)	0 = No 1 = Yes
How often Student Talks to Parents or Other Adults about Money Matters (Talk about Money)	2.49 (0.96)	1 = Never or hardly ever 2 = Once or twice a month 3 = Once or twice a week 4 = Almost every day
Learned to manage money in school (Learn about Money in School)	0.36 (0.48)	0 = No 1 = Yes
Student's Socioeconomic Status (ESCS)	-0.003 (16.59)	Index of economic, social, and cultural status

Note: Standard deviations in parentheses.
Note: ISCED stands for International Standard Classification of Education
Note: ISCED, level 3A = Upper secondary with access to level 5A (theoretically-oriented post-secondary); ISCED, level 3B = Upper secondary with access to level 5B (technically-oriented post-secondary); ISCED, level 3C = upper secondary with access to level 4 (post-secondary non-tertiary); ISCED, level 2 = lower secondary; ISCED, level 1 = primary education. For more information, see http://www.oecd.org/education/skills-beyond-school/1962350.pdf

In the sample, there is an equal distribution of male and female students. Mothers in this sample are, on average, more formally educated than fathers, with a mean of 4.31 for *Mother's Highest Schooling* and 4.23 for *Father's Highest Schooling*. The means for *Mother's Highest Schooling* and *Father's Highest Schooling* indicate that, on average, parents completed some form of secondary schooling, or a high school equivalent. Means for *Mother Employment* and *Father Employment* are 0.72 and 0.89, respectively. These means indicate that a higher percentage of fathers are employed than mothers. In the sample, under 40% of students learn to manage money in schools. Most students report having a mother living in their households (mean=0.96) and a father living in their households (mean=0.88). It should be noted that these variables indicate whether the student has a mother living in their home separately from whether or not the student has a father living in their home. To account for socioeconomic status, an index variable called *ESCS* was created by the OECD for use in the PISA dataset. The socioeconomic status index, *ESCS*, was created using principal component analyses from the highest occupational status of parents, the highest level of parental education in years, and an index measuring home possessions. In this sample, *ESCS* ranges from -5.67 to 3.35 with a targeted mean of 0. Positive values of *ESCS* indicate a student's socioeconomic status is above the average socioeconomic status of all students in the sample, while a negative number indicates that students are below the average socioeconomic status of all students in the sample (OECD, 2014a, 2014b).

Given that the chapter examines gender differences in demonstrated financial knowledge, I explore differences in average performance by gender and by country to see if gender gaps existed within countries. Table 4.3 shows average male performance, average female performance, the difference between average male and female performance, and whether or not that difference is statistically significant.

Table 4.3 Differences in Student Performance by Country and Gender, Restricted Sample, PISA 2012

Country (N=18)	Male	Female	Difference (Male – Female)
OECD Member Countries/Economies			
Australia	540.51	542.60	-2.08
Flemish Community (Belgium)	500.37	474.91	25.47
Czech Republic	505.29	500.73	4.56
Estonia	542.43	528.35	14.08
France	583.67	586.09	-2.42
Israel	508.48	519.42	-10.93
Italy	505.75	490.83	14.21***
New Zealand	483.80	475.75	8.05
Poland	494.67	483.71	10.96
Slovak Republic	480.46	477.80	2.66
Slovenia	483.03	480.04	2.99
Spain	507.31	503.65	3.66
USA	503.57	485.65	17.92*
Non-OECD Member Countries/Economies			
Columbia	541.74	530.22	11.52
Croatia	484.78	489.56	-4.78
Latvia	496.25	479.66	16.59*
Russian Federation	569.04	563.76	5.28
Shanghai-China	541.71	524.08	17.63*
Average	515.16	507.60	7.56***

Note: ***p<0.001, ** p<0.01, *p<0.05

Across the entire sample of students, there exists a statistically significant difference between the average male score and the average female score, indicating the presence of a traditional gender gap favoring men. Interestingly, only a few individual countries exhibit statistically significant differences in mean scores by gender. These countries are Italy, Latvia, the United States of America, and the Shanghai region of China. Some countries show gender gaps favoring women, but those gender gaps are not statistically significant.

4.3.2 Model Estimates

To examine variance within the sample, an unconditional model is built within a multilevel modeling framework. Unconditional models are equivalent to one-way ANOVAs. These types of models show the amount of variance both within and between schools (Raudenbush & Bryk, 2002). In order to estimate the amount of variance at each level of analysis, intraclass correlations (ICC) are calculated using an unconditional model. In this case, an unconditional model with the outcome of student financial knowledge is built without any predictor variables. According to this model, 61.53% of the variance in student achievement occurs at the student level and 30.50% of the variance in student achievement occurs at the school level. Thus, 7.97% [or 1-(0.6153-0.3050)] of the variance occurs at the country level. Recalling that this data is hierarchical in nature, student observations within the same school will share some of the variance. The same can be said for students within the same country. Results first indicate that most of the variance in financial knowledge can be accounted for at the student level, but a good portion of the variance can be explained at both the school and country levels. Since there is a significant portion of variance at both the school and country levels, multilevel modeling is appropriate for the dataset. Additionally, when weighted-cluster robust modeling is attempted, the procedure does not account correctly for the unequal variance or for the complex error terms. Thus, due to the clustered nature of the data and the variance at each level, multilevel modeling is the best methodology to use in the context of the dataset and the research questions.

Table 4.4 presents fixed effects results for a multilevel modeling analysis of how the student’s gender and parental characteristics are related to financial knowledge.

Table 4.4 Multilevel Regression Estimates of Predictors of Financial Knowledge, Fixed Effects, Parent Analyses, PISA 2012

	Model 1	Model 2	Model 3	Model 4
Fixed Effects				
Intercept	505.19****	499.95****	426.43****	427.31****
	(7.00)	(7.47)	(11.08)	(12.77)
ESCS	35.25****	34.11****	29.17****	29.01****
	(0.94)	(0.92)	(1.18)	(1.18)
Learn about Money in School	3.56*	3.73*	3.39	3.26
	(1.78)	(1.75)	(1.75)	(1.75)
Male		12.10****	12.53****	13.67
		(2.24)	(2.21)	(14.06)
Mother's Highest Schooling			3.50***	6.61****
			(1.17)	(1.48)
Mother Employment			6.07***	10.37****
			(1.97)	(2.61)
Father's Highest Schooling			3.47***	0.87
			(1.08)	(1.39)
Father Employment			-7.87**	-7.68*
			(2.74)	(3.56)
Mother Lives in Home			29.61****	29.16****
			(4.89)	(7.11)
Father Lives in Home			9.72***	5.77
			(2.62)	(3.46)
Talk about Money			3.44****	2.71**
			(0.89)	(1.19)
Male*Mother's Highest Schooling				-7.35***
				(2.19)
Male*Mother Employment				-7.88*
				(3.90)
Male*Father's Highest Schooling				6.01**
				(2.05)
Male*Father Employment				-1.20
				(5.53)
Male*Mother Lives in Home				0.003
				(9.81)
Male*Father Lives in Home				9.19
				(5.25)
Male*Talk about Money				1.47
				(1.78)
% of level-1 variance explained	0.10	0.30	0.31	0.31
% of level-2 variance explained	0.23	0.30	0.31	0.31

Note: ****p<0.001; ***p<0.01; **p<0.05; *p<0.10
Note: Standard errors in parentheses

In all of the models, a student's socioeconomic status (measured by the variable *ESCS)* and a student's opportunity to learn (measured by the variable *Learn* *about Money in School)* are controlled for in accordance with past research (Schmidt et al., 2011). Interestingly, the opportunity to learn measure chosen - whether or not students learned how to manage money in school - is only marginally significant in Models 1 and 2 and not significant in Models 3 and 4. Other measures of opportunity to learn, such as whether or not the student was exposed to financial education in schools, are examined to see if they better fit the model. Due to the vast differences in educational systems within the different countries and possibly even within the different schools, other measures such as the exposure to financial education cannot be used. Questions capturing possible opportunity to learn measures came in the school surveys, where administrators were asked as to whether or not their school offered financial education. An administrator indicating that their school offered some type of financial education is not necessarily indicative that students had the opportunity to learn the material being assessed on the PISA 2012 Financial Literacy Assessment. Furthermore, it could not be determined whether or not individual students were exposed to such financial education programs. Thus, whether or not a school offered financial education was not included in analyses. Though *Learn about Money in School* is marginally significant in Models 1 and 2 and insignificant in Models 3 and 4, the coefficient is positive in all models estimated. Socioeconomic status, however, is a significantly correlated with expected student financial knowledge in all models. Students with higher than average socio-economic status, on average, have higher expected scores on the PISA 2012 Financial Literacy Assessment. In fact, depending upon the model, a one-unit increase in *ESCS* is associated with an increase of between 29.01 and 35.25 points in expected student knowledge.

Model 1 explains around 10% of the variance at level 1, or at the student level, but the model explains 23% of the school-level variance.[9] Since *ESCS* and *Learn about Money in School* are both entered into the model as uncentered, the intercept of 505.19 indicates the mean outcome for a school if all the level-1 predictors are set to zero. Having a higher socioeconomic status *(ESCS)* is correlated with a large increase in average performance, as indicated by the coefficient of 35.25. In other words, this further proves the important relationship between financial knowledge and student socioeconomic status in this model. Students who learned about money in school saw modest expected increases in their financial knowledge.

Model 2 adds the student's gender (*Male)* as a predictor of student performance. On average, being a male is associated with an increase in performance by approximately 12 points, and this finding is statistically significant. Thus, gender is significantly correlated with a student's financial knowledge. The model's findings are consistent with previous findings that male students tend to have more financial knowledge than female students (Becchetti et al., 2013; Lührmann et al., 2012). In the PISA 2012 sample used here, there is a statistically significant difference in the scores of male and female student. Therefore, a gender gap is present for the entire sample of students in all schools and all countries. Socioeconomic status is once again highly correlated with the measure of financial knowledge, or student performance, in this model. An increase in student socioeconomic status is associated with a 34-point increase in performance. The addition of *Male* increases the percentage of level-1

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[9] Based on calculations of the percentage of variance explained at level-3, the models estimated were deemed to be poor fits for explaining variance at the country-level. Therefore, the percentage of level-3 variance explained is not presented in Table 4.3.

variance explained to 30%, thus increasing the predictive power of the model. The model also explains 30% of the level-2 variance. When comparing Model 2 to Model 1, the student's gender explains a great deal of variance at the student level in the sample of students.[10]

Model 3 adds variables to examine possible parental influence on student financial knowledge, as indicated by past research. Variables added include the highest levels of schooling for a student's mother and father, the mother and father's respective employment statuses, whether the student's mother lives in the student's household, whether the student's father lives in the student's household, and how often the student discusses money with their parents or with other adults. The gender gap in this model is essentially unchanged with male students outperforming female students by 12.53 points.

All of the parental characteristics are correlated with a student's financial knowledge in Model 3. The most compelling result is the correlation between having a mother live in the student's household and student financial knowledge. Having a mother live in the student's household is associated with 29.61 point increase in performance. Yet, most students report having a mother live in their home (mean of *Mother Lives in Home* = 0.96), so the coefficient on *Mother Lives in Home* should be modestly interpreted. There is a positive, significant correlation between having a father live in the student's household and student financial knowledge, but it is smaller than the correlation between *Mother Lives in Home* and student knowledge. The analyses do not examine whether or not the student had both parents living in their

[10] It should be noted that this represents a medium effect size (Cohen's d) and a large effect size index (Cohen's f^2).

households, as research questions focus on the differing influences of mothers and fathers and not on two-parent versus single-parent households. More work should be done in the context of financial knowledge in order to determine whether or not this result is generalizable.

The statistically significant correlations of the mother's highest level of schooling and the father's highest level of schooling are also worth noting. In this case, each change in educational level from one level to the next is associated with an increase of 3.50 points in expected student performance for the mother's education and an increase of 3.47 points in expected student performance for the father's education. Again, this result is limited as educational level variables are only reported up to the high school level. The mother's and father's employment statuses are also correlated with their child's financial knowledge. Having a working mother is associated with a 6.07-point increase in financial knowledge scores, while having a working father is associated with a 7.87-point decrease in financial knowledge. Finally, discussing money matters with parents or other adults is moderately related to a student's financial knowledge. Students who reported discussing money matters with their parents or other adults on a regular basis are associated with a 3.44-point increase in expected scores. However, the variable does not indicate how often money matters were discussed or the content of such discussions. Adding parental characteristics increases the amount of variance explained moderately at level 1 to 31% and to 31% at level 2, thus indicating that parental characteristics do help to explain student performance at the student and school levels.

Since past research has shown that parents can have differing influences on sons and daughters in terms of financial knowledge (Dotson & Hyatt, 2005; Jorgensen

& Savla, 2010; Newcomb & Rabow, 1999), Model 4 also examines whether or not there are relationships between a student's gender and parental characteristics. Model 4 adds interaction terms between the student's gender and parental characteristics. Before discussing interaction terms, it is important to examine the student and parental characteristics in Model 4. In terms of socioeconomic status, the story remains the same. However, Model 4 reports no statistical significance of being male.[11] In terms of parental characteristics, the mother's highest level of schooling, the mother's employment status, having a mother live in the student's household, and discussing money with parents remain positively correlated with student financial knowledge. The father's employment status continues to be negatively correlated with student financial knowledge. Interestingly, the father's highest level of schooling and having a father live in the household are no longer statistically significant in Model 4.

The first significant interaction is between a student's gender and mother's highest level of education. If the student is male and his mother is more highly educated, his score on the assessment is expected to decrease. To examine the interaction between being male and having a more educated mother, the coefficient of mother's highest level of schooling of 6.61 is added to the interaction term of -7.35. When adding these two coefficients together, the net influence is a small point decrease in the expected scores of male students for every change in the mother's education level. For the interaction between gender and a father's highest level of

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[11] The reason the gender gap is no longer present here is due to the centering of the *Male* variable in the multilevel model. If *Male* were centered differently or coded differently, the gender gap would be present, but the interaction terms would be difficult to interpret.

schooling, there will be an increase in financial knowledge for male students with highly educated fathers. The interaction term between the student's gender and the mother's employment status is marginally significant. This interaction term predicts that male students will not be as influenced by having a working mother as female students. Therefore, female students with working mothers are expected to have slightly more financial knowledge than male students with working mothers.

Table 4.5 examines the random effects, or variance components, of the models estimated for the school intercept, the country intercept, and whether or not gender varied among schools and among countries.

Table 4.5 Multilevel Regression Estimates, Error Variance, Parent Analyses, PISA 2012

	Model 1	Model 2	Model 3	Model 4
Error Variance/ Random Effects				
Level-1 (Residual)	5004.02 (62.08)	3933.34 (68.74)	3888.77 (67.98)	3876.18 (67.84)
Intercept (School)	2149.00*** (103.28)	1958.62*** (99.54)	1924.79*** (98.23)	1922.41*** (98.15)
Intercept (Country)	825.16*** (299.38)	937.33** (340.03)	935.57** (338.88)	929.20** (336.32)
Gender (School)	N/A	2949.36*** (181.46)	2936.28*** (179.60)	2964.22*** (180.10)
Gender (Country)	N/A	8.17 (25.89)	6.94 (24.48)	N/A

Note: ***p<0.001; **p<0.01; *p<0.05
Note: Level-1 residual values do not report statistical significance.
Note: Standard deviations in parentheses.

In all models tested, the school-intercepts and the country-intercepts are statistically significant, indicating that average scores vary across schools and across countries. One reason to examine the variance components is to justify the use of multilevel modeling. Because of the statistically significant variance estimates, multilevel modeling is appropriate for this data. While average performance does vary within the sample of schools and within the sample of countries, the same cannot be consistently said for the relationship between gender and financial knowledge. Models 2 – 4 indicate that the relationship between gender and financial knowledge does vary by school but does not vary by country. In Models 2 and 3, the variance component for gender at the country level was not statistically significant, and in Model 4, the country-level variance component for gender is not included due to singularity issues. Interpreting the variance components allows for a more complete picture of average financial knowledge and the influence of gender on financial knowledge within the sample.

4.4 Discussion

A persistent gender gap in both financial knowledge and financial literacy has appeared in a variety of populations around the world (Atkinson & Messy, 2012; Becchetti et al., 2013; Butters et al., 2012; OECD, 2013b). One goal of this chapter is to examine student performance and gender in order to determine whether or not there is a gender gap in student financial knowledge. In two of the three models that included gender, male students outperformed female students, as past research has suggested. The second goal of the chapter was to examine student financial knowledge and the gender gap in financial knowledge within the context of parental characteristics. Some variables are found to be positively correlated with overall student financial knowledge and the gender gap in financial knowledge, suggesting that parents may be able to positively influence their children’s financial knowledge.

In the sample of students from the PISA 2012 Financial Literacy Assessment, a gender gap in financial knowledge is found in Models 2 and 3, whereby male students outperformed female students. The gender gap present is consistent with research from previous international samples (Becchetti et al., 2013; Lührmann et al., 2012). What is unique about this research is that the sample represents the largest number of countries examined within the context of a gender gap in the financial knowledge of high school students. The gender gap present here represents a gap in knowledge across all students in all schools and all countries represented in the data. It is not clear whether or not specific students from certain countries contributed to the gender gap more than others, as gender was not included as a random variable by country. Subsequent research should focus on whether the student's home country has an influence on the gender gap in achievement. Since analyses focus on the gender gap in financial knowledge across the sample of students, it is difficult to cite specific policies that could aid in closing this gap. Given the vast differences in school policies as well as country policies, country-by-country analyses could better aid in answering questions as to which specific policies countries could target to close the gender gap in financial knowledge. This research points to a situation whereby male students are more financial knowledgeable than female students, thus indicating the gender gap in financial knowledge is an international issue across a sample of students from a variety of different, developed countries.

As previously mentioned, with international datasets, it is important to control for the socioeconomic status of the students as well as whether or not they have been exposed to the content covered on the assessment being given. According to Schmidt et al., (2011), both the students' socioeconomic status (SES) and the students' opportunity to learn (OTL) were controlled for, as these variables accounted for many differences across students in various countries. In fact, Schmidt et al. (2011) suggested these variables should be controlled for in all research comparing international educational outcomes. In all model estimates in this chapter, the students' socioeconomic status was positive and highly significant, indicating that students from more advantaged backgrounds are expected to have more financial knowledge. Moreover, socioeconomic status (*ESCS)* helps to explain a good amount of the variance within student scores on the PISA 2012 Financial Literacy Assessment. In the case of the students' opportunity to learn, the measure used, whether or not the student reported learning about financial matters in school, is not significant. Subsequent international assessments of financial knowledge should seek to find more accurate measures of a student's opportunity to learn.

Variables such as mother's highest level of schooling and father's highest level of schooling are shown to be positively correlated with a student's financial knowledge. This is consistent with past research, which showed relationships between increased parental education and increased financial knowledge of their child (Mandell & Klein, 2007; Tennyson & Nguyen, 2001). Yet, this finding is limited for two reasons. First, the father's highest level of schooling is only significant in Model 3 and not in Model 4. Second, the parents' educational attainment is only reported as high as secondary education. Both Mandell & Klein (2007) and Tennyson & Nguyen (2001) examined the correlation between having college-educated parents who graduated and a child's financial knowledge. It could be the case that the correlations present in this chapter might have been different if all information regarding whether or not a parent graduated from college was present. Future research should examine whether having parents who are college graduates leads to increases in student financial knowledge.

Having a mother live in the student's household is positively correlated with a student's financial knowledge, as measured by the PISA 2012 Financial Literacy Assessment. While past research indicates that parents could influence their children's consumer socialization (Denhardt & Jeffress, 1971; Moschis, 1985; Ward, 1975), no previous research specifically examines the mother's relationship to their child's financial knowledge. It may be that mothers really do influence their children's financial knowledge or it could be that having a mother live in the home with the child has an influence on overall knowledge. Thus, it is unclear as to what exactly the *Mother Lives in Home* variable in the PISA 2012 data is capturing. Examining a more specific influence parents potentially have on their child's financial knowledge, there is a positive correlation between financial knowledge and students who report discussing money matters with their parents or other adults. The finding is limited, however, as it does not specifically capture discussing money matters with parents only. Overall, however, results suggest that the characteristics of parents, such as the parent's education or whether or not the parent lives at home, are correlated with their child's financial knowledge.

When examining interactions between gender and parental characteristics, there are some significant results in regards to gender and the mother's highest level of schooling, gender and the mother's employment status, gender and the father's highest level of schooling, and gender and having a father live in a student's home. The interaction terms between gender and parental characteristics indicate that parents may influence male and female students differently. The parental characteristics presented in the dataset may not be the best to examine the relationships with student financial knowledge, as they do not directly measure impact on consumer socialization, or the process by which children learn about how to be consumers (Denhardt & Jeffress, 1971; Moschis, 1985; Ward, 1975). How often parents and other adults discussed money matters with their children is also positively correlated with financial knowledge, suggesting that perhaps parental influence on consumer socialization is a more explicit process rather than an implicit one. It could thus be important to develop policies encouraging parents to talk about money with their children. The specifics of policies would depend on the school and country the student inhabited. Opportunity to learn did not explain any additional amount of variance in student scores, though the variable *Learn about Money in School* was marginally significant in Models 1 and 2. The statistical significance of this variable suggests that either the opportunity to learn about financial matters has a small influence on financial knowledge or that this is not the best measure of a student's true opportunity to learn within their given school and given country.

The models estimated make use of multilevel models by examining whether or not average performance and gender varied by school and/or by country. The analysis showed that the level-2 intercept and the level-3 intercept randomly vary across schools in all specifications of regression models. Determining whether or not intercepts randomly vary is important to examine because this methodology can capture some of the differences in schools and in countries that could help justify the use of multilevel modeling. The relationship between financial knowledge and gender varied among the sample of schools, indicating that each school could have different gender gaps in financial knowledge. However, the gender gap did not randomly vary by country. While this chapter does not make use of random slopes of student-level predictors, random intercepts models were extensively examined to determine whether there was variance in school and country intercepts. Future research should examine both random intercepts and random slopes, as this could increase the predictive power of the models.

One limitation of this chapter is the sample sizes. Here, the sample of 9,929 students is smaller than the 29,041 students who originally completed the assessment. Due to a rotated design that was implemented, this dataset contains missing data for the variables of interest for this study. Future research should take into account the issue of missing data and consider different ways to increase the sample sizes. Another limitation lies with self-reported data. Students reported all of the information about parents rather than parents reporting this information. The intention was to administer parent surveys to all parents of students involved in the assessment. Due to unforeseen circumstances, only parents from the Flemish Community in Belgium, Croatia, and Italy reported information about themselves. This information could not be used in analyses in this chapter, as it was not representative of the entire sample. In the future, parent surveys should be administered to all parents in all countries in order to increase the sample size and deal with some of the issues with student self-reported data.

This assessment was the first large-scale international test of financial knowledge, and it represents an opportunity to examine questions about gender and financial knowledge around the world. Researchers have the opportunity to examine factors associated with differences in financial knowledge and how knowledge varies among students. In addition, the PISA 2012 Financial Literacy Assessment data allows for questions to be answered using multilevel modeling, which helps to further explain why scores vary across students in different schools and in different countries. This chapter contributes to the growing body of literature regarding international financial knowledge of high school students and factors that may be related to the gender gap in financial knowledge. In addition, the chapter examines the proper methodology for answering the research questions. Results indicate a prominent gender gap favoring males, which suggests policies targeting female students should be examined. In terms of parental characteristics, results indicate that parents may have a positive influence on their children's understanding of financial concepts. These compelling results help to depict financial knowledge in an international context as well as point to specific areas that policies could help to improve financial knowledge.

Chapter 5

DO GENDER AND COUNTRY-LEVEL VARIABLES INFLUENCE FINANCIAL KNOWLEDGE?

This chapter examines the relationship between gender and financial knowledge, but also examines the relationships between country-level variables and student financial knowledge. Guided by the research questions in this dissertation, this chapter focuses on answering the following research questions presented in Section 1.2.1 in Chapter 1:

1. How does financial knowledge vary by gender in students around the world?

3. Are country-level variables related to a student's understanding of financial matters? Are country-level variables related to gender differences in financial knowledge?

Section 5.1 provides an introduction and background material. Section 5.2 discusses the methodological approach to answering the research questions, including information about multilevel modeling, educational production functions, the planned analyses, and the estimation technique. Section 5.3 discusses descriptive statistics for the data used. Section 5.4 provides results of multilevel modeling for two samples, a large unrestricted sample of students and a smaller restricted sample identical to the sample in Chapter 4. In addition, Section 5.4 provides results for two different weighting strategies, one using both student-level and school-level weights, and one using only the student-level weight as was done in Chapter 4. The chapter concludes with a discussion of results and limitations in Section 5.5.

5.1 Introduction

Being financially knowledgeable is not just of individual concern, but it is also of global concern. The 2007-2009 Financial Crisis has shown the importance of understanding the global financial system in order to make well-informed financial decisions (Klapper, Lusardi, & van Oudheusden, 2015; Lusardi, 2011). In the United States, the subprime mortgage crisis and accompanying financial crisis have led to increased efforts to educate the American population about financial matters (Klapper et al., 2015; Lusardi & Mitchell, 2014). Elsewhere around the world, recent economic conditions and financial crises have led to concerns about individual financial knowledge. To provide a baseline for global financial knowledge, the Standard & Poor’s Ratings Service Global Financial Literacy Survey was administered to over 150,000 adults in 144 countries. The survey of five financial knowledge questions showed that adult financial knowledge scores ranged from 13% correct to 71% correct, with an average score of 55% correct in advanced countries and 28% correct in emerging economies (Klapper et al., 2015). Not only do the results point to a lack of financial knowledge, but results also suggest a link between the country one lives in and one’s financial literacy. Moreover, one’s country of residence and economic conditions appear to influence one’s financial knowledge.

Past research has indicated potential relationships between the economic landscape of a country and individual financial knowledge. For example, a possible relationship between a country’s per capita GDP and the financial knowledge of its people has been posited (Jappelli, 2010). Another link between a country’s unemployment rate and financial literacy was proposed, but the relationship could not be statistically proven in Chile (Behrman et al., 2010). Other studies have examined macroeconomic variables such as income inequality and average education level, but few correlations have been found (Atkinson & Messy, 2012; LoPrete, 2013; Lusardi & Mitchell, 2011). These studies were limited in their scope, as few countries were examined and relatively small samples were used. While correlations between a country's economic conditions and individual financial knowledge have been proposed, few concrete relationships have been identified.

Using the PISA 2012 Financial Literacy Assessment, this chapter examines country-level variables such as per capita GDP and the unemployment rate to determine if these variables influence a student's financial knowledge. Although no previous research pointed to a relationship between the gender gap in financial knowledge and country-level variables, the second goal of the chapter is to explore country-level variables within the context of the gender gap in financial knowledge. Analyses are done using hierarchical linear modeling (HLM), or multilevel modeling, to best account for the nested nature of the data, as multilevel modeling allows for the error term to be distributed to various levels of analysis (Gorard, 2003; Raudenbush & Bryk, 2002). Through the exploration of a country's economic landscape, a more accurate picture of the international financial knowledge of high school-aged students can emerge.

5.2 Methodology

5.2.1 Multilevel Modeling

Multilevel modeling has become increasingly popular in educational research, as most educational data is nested in hierarchical levels. Because of the nested nature of such data, an individual observation will share a certain amount of variance with other individual observations. For example, two students within the same school may have different individual characteristics, but, because the students attend the same school, the two will share certain school characteristics in common. Thus, individual observations are not necessarily independent of one another; in fact, students in the same school may even be more similar to one another than different (Hofman, 1997). Multilevel modeling accounts for shared characteristics, or variance, by estimating fixed effects at the lowest level (i.e. the student level) and then uses these fixed effects to estimate higher-level effects (Hofman, 1997; Woltman et al., 2012). In this study, fixed effects are first estimated at the student level (level 1) and then subsequently used in the estimation procedure to estimate effects at both the school level (level 2) and then the country level (level 3).

The multilevel modeling estimation procedure uses Bayesian estimation to estimate regression parameters as a weighted average of the group means and the overall mean (Raudenbush & Bryk, 2002). These types of estimates are more commonly known as shrinkage estimates. Because there are multiple groups within the data, each group's mean is also influenced by the data from other groups. It could be argued that this is analogous to estimating linear regression except that multilevel modeling adds an analysis of variance (ANOVA) for each of the clusters or levels (Raudenbush & Bryk, 2002). Multilevel models can also explore the links between different levels as opposed to controlling for a specific level (Michaelowa, 2001). Thus, to produce shrinkage estimates, the estimates "borrow strength" from other groups (Raudenbush & Bryk, 2002). To test whether or not this type of estimation is appropriate, either a likelihood ratio test or a Hausman test can be used to identify the best modeling procedure (Clarke et al., 2010; Gujarati & Porter, 2009; Raudenbush &

Bryk, 2002; Garson, 2013). More commonly, however, multilevel modeling is justified by estimating the variance explained at each level of analysis (Garson, 2013).

Student performance can be modeled with combinations of student-level variables, school-level variables, and country-level variables. With three possible levels of analysis present in the PISA 2012 Financial Literacy Assessment data, a variety of three level modeling can be estimated. The three levels of analysis in this chapter are the following: level 1 was the student level, level 2 was the school level, and level 3 was the country level. Typically in multilevel modeling, equations are estimated for each level of analysis. The general equations take the following forms:

Level 1 (students): $$Y_{ijk} = \pi_{0jk} + \pi_{1_{jk}} X_{ijk} + \varepsilon_{ijk} \quad (6)$$

Level 2 (schools): $$\pi_{jk} = \beta_{00k} + \mathrm{r}_{\mathrm{jk}} \quad (7)$$

Level 3 (countries): $$\beta_{00k} = \gamma_{000} + \gamma_{001} W_k + u_{00k} \quad (8)$$

where Y_{ijk} is a measure of financial knowledge for student *i* in school *j* in country *k*.

π_{0jk} is the intercept for school *j* in country *k*.

X_{ijk} is a vector of independent variables at the student level.

π_{1jk} are student-level fixed effects.

ε_{ijk} is the student-level random effect, or variance component.

B_{00k} is the mean achievement in country *k*.

r_{jk} is the school-level random effect, or variance component.

γ_{000} is the intercept for the country-level model.

γ_{001} is the country-level slope.

W_k is a vector of independent variables at the country level.

u_{00k} is the country-level random effect, or variance component.

When estimating outcomes at the student level, the level-1 equation (equation 6) is first estimated. In equation 6, the outcome is student performance, and the inputs are student-level individual characteristics. While the equation estimates the relationships between level-1 characteristics and the outcome variable, it does not account for the fact that observations are grouped at level 2. In the level-2 equation, or the school-level equation, the previously estimated student intercept and student slopes (fixed effects) are used as the outcome variables. The inputs used are school-level characteristics. Models of this type are often referred to as "intercepts-as-outcomes" and "slopes-as-outcomes" models (Hofman, 1997). The level-2 equations estimated are used to indicate school effects, but they do not account for the fact that individual observations may have a higher level of grouping above level 2. Therefore, separate level-3 equations are estimated. The level-3 equations make use of the school effects as independent variables to estimate the country effects. In other words, the country-level fixed effects are estimated as part of the school equations. This chapter makes use of both intercepts-as-outcomes models to model average student performance across all countries sampled, as well as slopes-as-outcomes models to examine the gender gap in achievement. It should be noted that slope-as-outcomes models are frequently used to estimate individual interaction terms.

An advantage of multilevel modeling is that the estimation procedure allows for the estimation of fixed effects as well as random effects (Clarke et al., 2010). Random effects allow for questions to be answered as to whether or not variables vary within and across the different levels of analysis. Random effects are analogous to error terms in typical OLS regression, except that there are multiple error terms in each multilevel model. For example, Equations (6), (7), and (8) each contain their own error term, indicating that there is variance at each level of analysis. Exploring random effects allows researchers to look at whether or not a factor varies above the level of the outcome variable. In the context of this chapter, random effects will show a more complete picture of how much independent variables vary at the school level and the country level.

5.2.2 Educational Production Function

To estimate a student's performance on an assessment, educational production functions are commonly used. In educational production functions, the output refers to the student's performance, while the inputs are characteristics unique to the student, their school, and their country. Hanushek (1979, 1986) extensively studied educational production and was the first to determine that better educational "inputs" produced better student outcomes. To date, there is no specific functional form for educational production functions, and the output can be expressed in either continuous terms or in terms of educational attainment levels (Hanushek, 1997; Hedges, 1994; Krueger, 1999; Rothstein, 2010).

To estimate the relationships between country-level variables, student financial knowledge, and the gender gap in financial knowledge, educational production functions are estimated. In a multilevel modeling framework, equations are estimated at each level of analysis. As such, separate equations are estimated at the student level, the school level, and the country level. Additionally, slopes-as-outcomes models are estimated to examine factors contributing to a potential gender gap in financial knowledge. The equations follow the functional form from Raudenbush & Bryk (2002) in a multilevel modeling framework. More specifically, the student-level equation takes the following form:

$$Y_{ijk} = \pi_{0jk} + \pi_{1jk}(a_{ijk}) + \varepsilon_{ijk} \quad (9)$$

where Y_{ijk} is a measure of financial knowledge for student i in school j in country k.

π_{0jk} is the intercept for school j in country k.

a_{ijk} is a vector of independent variables at the student level.

π_{1jk} are the student-level fixed effects.

ε_{ijk} is the student-level random effect (or variance).

The school-level equations make use of the fixed effects from the student level in their estimate. They thus take the following forms:

$$\pi_{0jk} = \beta_{00k} + r_{0jk} \quad (10)$$

$$\pi_{1jk} = \beta_{10k} + r_{1jk} \quad (11)$$

where π_{0jk} is the intercept for school j in country k.

π_{1jk} is the slope for school j in country k.

β_{00k} is the intercept for the school intercept for school j in country k.

β_{10k} is the intercept for the school mean for school j in country k.

r_{0jk} - r_{1jk} are the school-level random effects (or variance).

The country-level effects are modeled using separate equations and make use of the level-2 equations as outcomes. The equations take the following forms:

$$\beta_{00k} = \gamma_{000} + \gamma_{001}(W_{1k}) + u_{00k} \quad (12)$$

$$\beta_{01k} = \gamma_{010} + \gamma_{011}(W_{1k}) + u_{01k} \quad (13)$$

$$\beta_{10k} = \gamma_{100} + \gamma_{101}(W_{1k}) + u_{10k} \quad (14)$$

$$\beta_{11k} = \gamma_{110} + \gamma_{111}(W_{1k}) + u_{11k} \quad (15)$$

where γ_{000} is the average country intercept for country k.

W_{1k} is a vector of independent variables at the country level.

γ_{001} is the average effect of W on the country intercept.

γ_{010} is the average country slope.

γ_{011} is the average effect of W on the average country slope.

γ_{100} is the average intercept between countries.

γ_{101} is the average effect of W on the intercept between countries.

γ_{110} is the average difference between the countries' slopes.

γ_{111} is the average effect of W on the average difference between the countries' slopes.

$u_{00k} - u_{11k}$ represent the country-level random effects.

5.2.3 Analyses

For the purpose of this chapter, three-level multilevel models are estimated to examine differences across the international sample of students. Estimates provide a view of students both within schools and within countries. To explore the gender gap in achievement, student-level and country-level variables are examined in the context of slopes-as-outcomes models in order to observe possible contributions to the gender gap in financial knowledge. Each model represents an educational production function with a continuous outcome variable of plausible values (PV) of student performance on the PISA 2012 Financial Literacy Assessment. Student performance is a measure of a student's financial knowledge.

Similar to previous research on international comparisons of student achievement, socioeconomic status of the student (SES) was controlled for in all models estimated (Schmidt et al., 2011). Previous attempts to control for the opportunity to learn (OTL) in Chapter 4 yielded no accurate estimate of such a measure; additionally, the OTL measure used did not account for any additional variance explained at the student level, and thus, no measure of OTL is included in any of the models. If a variable does not explain additional variance in multilevel modeling, it is typical excluded from subsequent analyses (Garson, 2013).

5.2.4 Estimation Technique

For the purpose of this chapter, analyses are conducted in the HLM 7 statistical software using the HLM3 procedure for three-level multilevel models. The outcome variable is represented by five different PV intervals. HLM 7 allows for a dependent variable to be a series of PVs, and each run of the model with a different PV is averaged to output the final model. The HLM 7 software uses restricted maximum likelihood estimation (REML), which is the basis for estimation in multilevel modeling. HLM 7 software also begins with the average of OLS estimates for the starting values in the estimation process rather than a value of zero (Garson, 2013). As with analyses in Chapter 4, two different weighting strategies are utilized in this chapter. First, the student-level weight and the school-level weight are used to account for different sample sizes at each level. At the student level, PISA 2012 used a final weight and 80 replicate weights. Following the advice of statisticians at the OECD, results here use the finalized weight only. Models were run using each of the replicate weights at the student level, and results were almost identical. Unlike the many replicate weights at the student level, only one school-level weight is provided for use in these analyses.

The second weighting strategy uses only the finalized student-level weight in order to make more direct comparisons to results in Chapter 4. When using the SAS® 9.2 software, only a root-level weight can be used in multilevel modeling (Uekawa, 2004). While the HLM7 software can use more than one weight, analyses are also conducted with only the student-level weight to discuss the most appropriate weighting strategy in any subsequent analyses.

It should be noted that the statistical power of the models estimated may be limited due to the small sample size at level 3 (the country level). When estimating multilevel models, the typical rule of thumb is to ensure that there are at least 30 observations or groups at each level of analysis (Bell, Morgan, Kromrey, & Ferron, 2010; Maas & Hox, 2005). However, given the limited number of countries that administered the PISA 2012 Financial Literacy Assessment, it was not possible to increase the number of groups (or countries) at level 3. Through a series of simulation studies, some authors argue that decreasing the number of groups will bias estimates (Bell, Morgan, Kromrey et al., 2010; McNeish & Stapelton, 2014), but others argue that this is not the case (Maas & Hox, 2005; Bell, Morgan, Schoeneberger, Loudermilk, Kromrey, & Ferron, 2010). However, most agree that decreasing the number of groups for analysis will reduce the statistical power of the models (Snijders, 2005; Bell, Morgan, Schoeneberger et al., 2010). These simulation studies were conducted for 2-level multilevel models and are theoretical in nature rather than applied. Therefore, findings from previous research may not accurately apply to the models estimated in this chapter. Given the fact that it was impossible to increase the sample size at level 3, other measures are taken to ensure unbiased estimates and increased statistical power. When using the SAS® software, the Satterthwaite method is used to account for small sample sizes (Maas & Hox, 2005). When using both SAS® and HLM7, restricted maximum likelihood estimation (REML) is also used to account for differing sample sizes (McNeish & Stapelton, 2014).

Additionally, model diagnostics are run to determine if the model specifications were correct. Since multilevel modeling is used, heteroscedasticity is not checked in any of the models estimates. Since multilevel modeling already accounts for and corrects unequal variances in the structure of the nested data, heteroscedasticity is not an issue for concern. Residuals at all levels of analysis were examined and appear to be normally distributed. Thus, no additional examination of any of the residuals is necessary. As with previous work that used the PISA 2012 data, some individual observations exhibited high influence on the data. However, upon further examination and through the use of a finalized weight, none of the individual observations raised great concern, as there were no changes to fixed effects and minimal changes to the random effects. Since this research only focuses on whether or not random effects are significant, and does not interpret the random effects beyond their significance, the changes in the random effects estimates are not a concern in answering the research questions.

5.3 Descriptive Statistics

In the PISA 2012 Financial Literacy Assessment, a total of 29,041 students from 5,260 schools in 18 countries completed the assessment. Given missing data at the student level, the sample size used in analyses is smaller than the original sample. The new sample, henceforth referred to as the unrestricted sample, includes 27,057 students from 4,927 schools in 18 countries. The missing data occurs at the student level. Analyses are also run on a restricted sample of 9,929 students from 3,964 schools in 18 countries. The restricted sample of students was used in Chapter 4 to examine the influence of parental characteristics on student financial knowledge and the gender gap in financial knowledge. When comparing means of the new unrestricted sample with the original sample, all of the means were the same. Table 5.1 presents sample sizes for both schools and students within each country in the unrestricted sample.

Table 5.1 Sample Sizes for Schools and Students within Countries, Unrestricted Sample, PISA 2012

Country (N=18)	Number of participating schools	Number of participating students
OECD Member Countries/Economies		
Australia	745	3,132
Flemish Community (Belgium)	155	1,042
Czech Republic	240	1,007
Estonia	200	1,080
France	199	934
Israel	153	987
Italy	1,061	6,474
New Zealand	156	827
Poland	165	991
Slovak Republic	218	1,018
Slovenia	289	1,237
Spain	165	1,016
United States	151	1,071
Non-OECD Member Countries/Economies		
Colombia	315	1,902
Croatia	160	1,126
Latvia	190	895
Russian Federation	212	1,138
Shanghai-China	153	1,180
Total	4,927	27,057

As Table 5.1 indicates, sample sizes vary greatly among countries and among schools. In terms of the number of schools, Italy has the largest number of schools at 1,061. The United States has the smallest number of schools with 151 American schools represented. Not surprisingly, differing school sample sizes led to differing numbers of students participating within individual countries. Italy, once again, has the most students at 6,474 students, while New Zealand has the fewest students with 827 participating. Due to the differing sample sizes both at the student level and the school level, student and school weights are provided in the dataset for subsequent analyses.

For more accurate comparisons, a restricted sample is also examined. The restricted sample used is the same subsample of students examined in Chapter 4. It should be noted that the sample was restricted in Chapter 4 due to missing data in the variables of analysis. Most of the missing data came from a student money management survey that accompanied the assessment. The survey was two pages in length, and students were asked to either complete the first page or the second page. Due to this action, the original sample size was cut in half. After that, any individual observation with additional missing parental characteristics data was removed from the sample. Table 5.2 presents sample sizes for both schools and students within each country for the restricted sample used in analyses.

Table 5.2 Sample Sizes for Schools and Students within Countries, Restricted Sample, PISA 2012

Country (N=18)	Number of participating schools	Number of participating students
OECD Member Countries/Economies		
Australia	148	248
Flemish Community (Belgium)	29	53
Czech Republic	282	541
Estonia	204	432
France	229	433

Table 5.2 continued

Israel	30	54
Italy	1,061	3,149
New Zealand	148	344
Poland	181	449
Slovak Republic	184	431
Slovenia	256	558
Spain	188	441
United States	153	462
Non-OECD Member Countries/Economies		
Colombia	176	431
Croatia	190	517
Latvia	162	382
Russian Federation	167	398
Shanghai-China	176	606
Total	3,964	9,929

Table 5.2 is identical to Table 4.1 in Chapter 4. Once again, sample sizes within and among countries vary greatly. In the smaller sample of 9,929 students from 3,964 schools in 18 countries, Italy has the largest number of students and schools, with 3,149 and 1,061, respectively. Here, the fewest number of students represented comes from the Flemish Community of Belgium. The Flemish Community of Belgium has 53 students from 29 schools. Again, the restricted sample is used here to more easily compare results here to those from Chapter 4.

The variables of interest in subsequent analyses occur at the student level and the country level. At the student level, the student's gender (*Male*) and the student's socioeconomic status (*ESCS*) are examined. The variable of *ESCS* represents an index created by the OECD for use in the PISA dataset. The OECD created the *ESCS* variable through the use of principal component analyses. Components included were the highest occupation status of the student's parents, the highest level of parental education, and an index measuring home possessions. At the country level, several variables are included to indicate a country's economic health at the time the assessment was administered. The variables used include GDP per capita (*GDP)*, labor force participation rate (*LFPR*), labor force participation rate for women (*LFPRw*), the unemployment rate (*Unemployment*), and whether or not the country is an OECD member (*OECD*). With the exception of *OECD*, all country variables were obtained from the World Bank. The variable *OECD* is included in the original PISA Financial Literacy data. *GDP* represents the per capita GDP in 2011, and is measured in constant 2005 U.S. dollars. *LFPR* represents the International Labour Organisation's (ILO) estimate of the percentage of all individuals 15 years or older who were members of the labor force in 2011, the year of analysis. *LFPRw* is similar to *LFPR*, except that it represents the percentage of females 15 years or older who were members of the labor force in 2011. The variable *Unemployment* represents the percentage of the total labor force that was not employed but actively seeking work in 2011. Table 5.3 depicts the means and standard deviations for all variables of interest for both the unrestricted sample and the restricted sample.

Table 5.3 Sample Means, Country Analyses, PISA 2012

Student-Level Variable	Mean (unrestricted) (n=27,057)	Mean (restricted) (n=9,929)	Explanation
Male	0.50 (0.50)	0.50 (0.50)	0 = Female 1 = Male
Student's Socioeconomic Status (ESCS)	-0.08 (0.96)	0.00 (0.94)	Index of economic, social, and cultural status
Country-Level Variable	**Mean (unrestricted) (n=18)**	**Mean (restricted) (n=18)**	**Explanation**
GDP	$20,437.27 (12,858.23)	$20,437.27 (12,858.23)	GDP Per Capita 2011 (in constant 2005 US$)
LFPR	0.60 (0.06)	0.60 (0.06)	Labor Force Participation Rate (%)
LFPRw	0.53 (0.06)	0.53 (0.06)	Labor Force Participation Rate - Women (%)
Unemployment	0.10 (0.04)	0.10 (0.04)	Unemployment Rate (%)
OECD	0.72 (0.46)	0.72 (0.46)	0 = non-OECD member 1 = OECD member

Note: GDP, LFPR, LFPRw, and Unemployment were obtained via the World Bank at http://data.worldbank.org/
Note: Standard deviation in parentheses.

With the exception of *ESCS*, all means and standard deviations for the unrestricted sample and the restricted sample are the same. The identical means can in part be attributed to the fact that all 18 countries are represented in both the unrestricted and restricted samples. Since students from the same country share common country characteristics, means of country-level variables remain the same between the two samples. The mean of *ESCS* is difficult to interpret, as it is an indexed variable depicting the socioeconomic status of a student. The mean for *ESCS* in the unrestricted sample is -0.08, while the mean for *ESCS* for the restricted sample was 0.00. In both the unrestricted and restricted samples, half of the students are female and half are male. The equal split was intentional, as the OECD targeted equal numbers of male and female students for the assessment. The average *GDP* per capita is just over $20,000. This *GDP* per capita is relatively high for an international sample; however, given that the sample of countries is mostly developed, industrialized countries, the high mean is expected. Around 72% of the students in the sample came from OECD member countries, which again is expected given the high *GDP* average. Across the sample of countries, the average *LFPR* is 60%. Thus, 60% of those over 15 years old are members of the labor force. Given the fact that women still have lower labor force participation rates than men, *LFPRw* is, not surprisingly, lower at an average of 53%. The average unemployment rate in 2011 was 10%. The average unemployment rate was high at the time as many of the countries in the sample were experiencing the effects of the recent global recession.

Given that one of the research questions in this dissertation examines gender differences in demonstrated financial knowledge, I examined gender differences in demonstrated financial knowledge by gender for both the unrestricted and restricted samples. Table 5.4 shows average male performance, average female performance, the difference between average male and female performance, and whether or not this difference is statistically significant within the unrestricted sample.

Table 5.4 Differences in Student Performance by Country and Gender, Unrestricted Sample, PISA 2012

Country (N=18)	Male	Female	Difference (Male – Female)
OECD Member Countries/Economies			
Australia	517.50	519.62	-2.12
Flemish Community (Belgium)	553.31	543.17	10.14
Czech Republic	533.57	522.83	10.74
Estonia	529.63	532.51	-2.88
France	490.98	493.23	-2.25
Israel	485.35	483.01	2.34
Italy	478.28	468.29	9.99***
New Zealand	529.45	524.69	4.77
Poland	516.07	512.53	3.53
Slovak Republic	472.20	477.00	-4.80
Slovenia	465.63	474.30	-8.67
Spain	488.07	485.44	2.63
USA	493.43	493.01	0.42
Non-OECD Member Countries/Economies			
Columbia	398.11	392.07	6.04
Croatia	482.14	478.98	3.16
Latvia	494.94	505.65	-10.71**
Russian Federation	486.31	487.98	-1.67
Shanghai-China	601.45	602.38	-0.93
Average	500.91	499.82	1.09*

Within the unrestricted sample, there exists no statistically significant difference between the average scores of male and female students across the sample of students. Despite this, two countries have statistically significant differences in the mean scores for male and female students: Italy and Latvia. Interestingly, the gender gap in Italy favors male students, while the gender gap in Latvia favors female students.

The gender differences in demonstrated financial knowledge within the restricted sample of students present a different picture. Table 5.5 shows demonstrated performance by gender as well as differences between male and female performance for the restricted sample.

Table 5.5 Differences in Student Performance by Country and Gender, Restricted Sample, PISA 2012

Country (N=18)	Male	Female	Difference (Male – Female)
OECD Member Countries/Economies			
Australia	540.51	542.60	-2.08
Flemish Community (Belgium)	500.37	474.91	25.47
Czech Republic	505.29	500.73	4.56
Estonia	542.43	528.35	14.08
France	583.67	586.09	-2.42
Israel	508.48	519.42	-10.93
Italy	505.75	490.83	14.21***
New Zealand	483.80	475.75	8.05
Poland	494.67	483.71	10.96
Slovak Republic	480.46	477.80	2.66
Slovenia	483.03	480.04	2.99
Spain	507.31	503.65	3.66
USA	503.57	485.65	17.92*
Non-OECD Member Countries/Economies			
Columbia	541.74	530.22	11.52
Croatia	484.78	489.56	-4.78
Latvia	496.25	479.66	16.59*
Russian Federation	569.04	563.76	5.28
Shanghai-China	541.71	524.08	17.63*
Average	515.16	507.60	7.56***

Table 5.5 is identical to Table 4.3 from Chapter 4. Within the restricted sample across the entire sample of students, a statistically significant difference between the

overall average male score and the overall average female score exists. Interestingly, the restricted sample shows a gender gap across all students that favors men, while the unrestricted sample shows no gender gap.

5.4 Model Estimates

To examine student financial knowledge and corresponding country-level variables, three multilevel models are built. First, to examine student performance and the gender gap in achievement, a model including the student's gender (*Male*) and socioeconomic status (*ESCS*) is estimated (Model 1). Both of these variables are grand-mean centered in order to examine the entire sample of students. Instead of comparing each student to students within their own school, grand-mean centering is used to compare each student within the sample regardless of which school they attended or their country of residence. To examine the correlations between country-level variables and financial knowledge, Model 2 includes *OECD, GDP*, *LFPRw,* and *Unemployment.* Some research has shown that students, especially female students, may be influenced by their mother's financial and employment decisions (Becchetti et al., 2013; Dotson & Hyatt, 2005; Huang et al., 2013). *LFPRw* represents a way to examine the role of women in the economy and the influence that women, particularly mothers, could have on a student's financial knowledge as well on the gender gap in financial knowledge. Once again, each of these variables is entered into the model as grand-mean centered. In addition to including the relationships between country-level variables and average student performance, the relationships between country-level variables and the gender gap in achievement are also examined. Model 3 is similar to Model 2 except that *LFPR* was included instead of *LFPRw*. Given the fact that each country has many cultural differences that cannot be accounted for, *LFPRw* is used as a proxy for the status of women in the economy.

5.4.1 Unrestricted Model Estimates – Student- and School-Level Weights

Estimates presented in this section contain models using both student- and school-level finalized weights and using the unrestricted sample of students. In order to account for the variability in results prior to any estimation, unconditional (or null) models are built, where the outcome of student performance was added with no independent explanatory variables. Through the estimations of variance components, the amount of variance in student financial knowledge at each level of analysis is determined. In the unrestricted sample, 53% of the variance in student knowledge occurs at the student level of analysis. An additional 35% of variance in student knowledge occurs at the school level, and the remaining 12% of variance occurs at the country level. Since there is a significant amount of variance accounted for above the student level of analysis, the use of multilevel modeling is justified in the sample. If almost all of the variance were to occur at the student level, multilevel modeling would not be appropriate for the sample.

To examine the financial knowledge of students who completed the PISA 2012 Financial Literacy Assessment and corresponding country-level variables, a series of multilevel models are built. Table 5.6 presents multilevel regression estimates using both student- and school-level weights for the unrestricted sample.

Table 5.6 Multilevel Regression Estimates of Predictors of Financial Knowledge, Fixed Effects, Unrestricted Sample, Country Analyses, Student- and School-Level Weights, PISA 2012

	Model 1	Model 2	Model 3
Fixed Effects			
Level 1			
Intercept	473.31**	477.85**	481.81**
	(6.57)	(10.54)	(11.86)
Male	-0.01	0.68	0.53
	(1.38)	(3.22)	(3.15)
ESCS	29.80**	29.74**	29.83**
	(3.86)	(4.59)	(4.55)
Level 3 – Intercept-as-Outcome			
GDP		-0.002	-0.001
		(0.001)	(0.001)
OECD		77.14*	30.84
		(31.59)	(36.16)
LFPRw		420.09	
		(258.23)	
LFPR			-109.91
			(282.48)
Unemployment		-140.99	-120.29
		(189.42)	(201.55)
Level 3 – Gender Slope-as-Outcome			
GDP		-0.0002	0.0002
		(0.0004)	(0.0004)
OECD		1.34	5.37
		(9.25)	(9.74)
LFPRw		-7.12	
		(53.62)	
LFPR			32.41
			(72.93)
Unemployment		-5.66	-12.20
		(61.59)	(60.00)
% of level-1 variance explained	0.18	0.18	0.18
% of level-2 variance explained	0.31	0.31	0.34
% of level-3 variance explained	0.32	0.42	0.32

Note: **p<0.001; *p<0.01
Note: Standard error in parentheses.

First, a model controlling for the student's gender and socioeconomic status (*ESCS*) is built. In the unrestricted sample, the level-1 intercept and *ESCS* are significant. Given that the independent variables entered the model as grand-mean centered, the intercept indicates the mean outcome for a student across the sample of schools and countries. Thus, on average, students scored 473.31 points. The coefficient on *ESCS* is positive and indicates that being a student from higher socioeconomic backgrounds is associated with higher average financial knowledge. *Male* is not significant in this model specification, indicating that there is no gender gap in achievement in the unrestricted sample.

Model 2 added country-level variables to examine the relationships between a country's economic situation and average student performance, as well as to examine how males and females score on the assessment. Once again, the average performance (intercept) and *ESCS* are positive and significant, indicating similar findings to those in Model 1. When examining the intercept as an outcome, whether or not the country is an OECD member country is significantly correlated with average student performance. The coefficient of 77.14 indicates that being a student from an OECD country is associated with an increase in financial knowledge scores by around 77 points. Yet, the finding is only marginally significant. Interestingly, no other country-level variables are significantly correlated with average student performance. When examining the gender slope as the outcome variable, none of the country-level variables are significantly correlated with gender. These results seem to suggest that the economic conditions within specific countries have little to no relationship with the gender gap. This is not surprising given that a gender gap in achievement is not significant in this sample. Model 3 yields similar results to Model 2. Once again, none of the country-level variables are significantly correlated with either the intercept or the gender slope.

Each of the models explained some variance at each level of analysis. In Model 1, for example, 18% of the variance at the student level is explained by *ESCS* and *gender.* Model 1 also explains 31% of the variance at the school level and 32% of the variance at the country level. Interestingly, across subsequent models, the amount of student-level variance explained is constant at 18%. No additional variance in student scores is explained by the addition of any of the country-level variables. However, adding country-level variables did explain additional variance at both the school level and the country level; therefore, the correlations (or fixed effects) present in this model should be interpreted cautiously. With the addition of country-level variables in Model 2, the amount of variance explained at the country level remains the same at 31%, but the amount of variance in student scores at the country level increases to 42%. In Model 3, more variance at the country level is explained when replacing *LFPRw* with *LFPR,* but no additional variance is explained at the student level. Overall, these models do explain some of the variance at each level of analysis, though the sizes of the effects presented are small due to the small amount of variance explained and the small standard errors presented.

Table 5.7 shows the variance components, or random effects, at the school level and the country level for the intercepts and gender variable using both the student- and school-level weights for the unrestricted sample.

Table 5.7 Multilevel Regression Estimates of Predictors of Financial Knowledge, Error Variance, Unrestricted Sample, Country Analyses, Student- and School-Level Weights, PISA 2012

	Model 1	Model 2	Model 3
Error Variance/Random Effects			
Level-1 (Residual)	4468.24	4468.51	4468.38
	(66.84)	(66.84)	(66.85)
Intercept (Level 1 & 2)	2501.23**	2504.33**	2505.22**
	(50.01)	(50.04)	(50.05)
Gender (Level 1 & 2)	2203.94**	2188.17**	2186.61**
	(46.95)	(46.78)	(46.76)
Intercept (Level 3)	821.99**	702.43**	857.33**
	(28.67)	(26.50)	(29.28)
Gender (Level 3)	1.61	0.65	1.32
	(1.27)	(0.81)	(1.15)

Note: **p<0.001; *p<0.01
Note: Level-1 residual values do not report statistical significance.
Note: Standard deviation in parentheses.

In each of the three models estimated, the school intercepts and the country intercepts have statistically significant variance components. The statistical significance indicates that average scores for students vary depending on the school and the country. Statistically significant variance components justify the use of multilevel modeling, as OLS cannot account for random effects. Gender randomly varies at the school level but not at the country level. In other words, the influence of gender on financial knowledge does vary by which school the student attends but it does not vary by country. Future research could examine performance by gender within certain schools or within certain countries rather than across the entire sample of schools and countries to test the gender variance.

5.4.2 Unrestricted Model Estimates – Student-Level Weight

Estimates presented in this section contain models using only the finalized student-level weight and using the unrestricted sample of students. Unconditional models are first built to determine the amount of variance at each level of analysis within the unrestricted sample. The amount of variance at each level, obtained through the estimation of unconditional models and intraclass correlations, are the following: 51% at the student level, 31% at the school level, and 18% at the country level. These numbers are slightly different than the intraclass correlations in Section 5.4.1.

As with results in Section 5.4.1, a series of multilevel models are built to examine performance on the PISA 2012 Financial Literacy Assessment. Table 5.8 presents multilevel regression estimates for the unrestricted sample using only the student-level weight.

Table 5.8 Multilevel Regression Estimates of Predictors of Financial Knowledge, Fixed Effects, Unrestricted Sample, Country Analyses, Student-Level Weight, PISA 2012

	Model 1	Model 2	Model 3
Fixed Effects			
Level 1			
Intercept	495.51***	495.81***	495.76***
	(9.21)	(15.25)	(11.01)
Male	3.58*	3.31*	3.45*
	(1.38)	(1.28)*	(1.23)
ESCS	25.67***	25.57***	25.61***
	(1.89)	(2.73)	(2.18)
Level 3 – Intercept-as-Outcome			
GDP		0.0001	0.00004
		(0.001)	(0.0008)
OECD		23.96	17.91
		(28.55)	(26.32)
LFPRw		387.26	
		(326.20)	
LFPR			260.26
			(213.68)
Unemployment		-97.62	-145.90
		(206.18)	(173.53)

Table 5.8 continued

Level 3 – Gender Slope-as-Outcome			
GDP		-0.00004 (0.0001)	-0.00005 (0.0001)
OECD		0.50 (4.09)	0.66 (16.38)
LFPRw		-42.28* (14.29)	
LFPR			-40.46* (16.38)
Unemployment		-49.48 (31.01)	-48.88 (31.94)
% of level-1 variance explained	0.05	0.05	0.05
% of level-2 variance explained	0.26	0.26	0.26
% of level-3 variance explained	0.18	0.27	0.25

Note: ***p<0.001; **p<0.01; *p<0.05
Note: Standard error in parentheses.

Model 1 again controls for the student's gender (*Male*) and socioeconomic status (*ESCS*). Using only the student weight for Model 1, the level-1 intercept, *Male*, and *ESCS* are all positive and significant at different levels of statistical significance. The level-1 intercept indicates that the average performance for a student across the sample of schools and countries is 495.51. The coefficient on *Male* indicates that male students outperform female students by 3.58 points. This finding indicates that there is a statistically significant gender gap present in this sample. Finally, the coefficient on *ESCS* is significant, indicating that students from higher socioeconomic backgrounds tend to score higher than those from lower socioeconomic backgrounds.

Model 2 adds country-level variables to examine the relationships between a country's economic situation and average student performance, as well as to examine how males and females score on the assessment. Once again, the level-1 intercept, *Male*, and *ESCS* are positive and significant at different levels of statistical significance. When examining the intercept as an outcome, none of the country-level variables are correlated with average student performance. When examining the gender slope as the outcome variable in order to possibly explain the gender gap in achievement that is present, only *LFPRw* is significantly correlated with gender. The coefficient on *LFPRw* indicates that for each increase in the female labor force participation rate, the gender gap, or difference between male and female students, is expected to decrease by 42.28 points. The finding, however, is only marginally significant.

Model 3 yields similar results to Model 2. Once again, none of the country-level variables are correlated with the intercept. However, in Model 3, an increase in the overall labor force participation rate is associated with a decrease in the gender gap, or difference between male and female students, by 40.46 points. Once again, this finding is only marginally significant. Both Models 2 and 3 indicate that labor force participation rate may help to explain the gender gap, but more work should be done to determine the true relationship present.

Each of the models explained some variance at each level of analysis. Models 1 – 3 all explained 5% of the student-level variance and 26% of the school-level variance. Model 1 explained 18% of the country-level variance, while Model 2 explained 27% of the country-level variance, and Model 3 explained 25% of the country-level variance. Once again, the models explain some variance at each level, but the estimates should be interpreted cautiously due to the small amount of variance explained and the small standard errors.

Table 5.9 presents the variance components, or random effects, at the school level and the country level for the intercepts and gender variable when only using the student-level weight on the unrestricted sample.

Table 5.9 Multilevel Regression Estimates of Predictors of Financial Knowledge, Error Variance, Unrestricted Sample, Country Analyses, Student-Level Weight, PISA 2012

	Model 1	Model 2	Model 3
Error Variance/Random Effects			
Level 1 (Residual)	5157.28	5157.31	5158.02
	(71.81)	(71.81)	(71.82)
Intercept (Level 1 & 2)	2441.36***	2439.21***	2440.42***
	(49.41)	(49.39)	(49.40)
Gender (Level 1 & 2)	292.03*	289.39*	284.97*
	(17.09)	(17.01)	(16.88)
Intercept (Level 3)	1544.65***	1379.05***	1412.24***
	(39.30)	(37.14)	(37.58)
Gender (Level 3)	11.52**	2.56	3.02
	(3.39)	(1.60)	(1.74)

Note: ***p<0.001; **p<0.01; *p<0.05
Note: Level-1 residual values do not report statistical significance.
Note: Standard deviation in parentheses.

In each of the three models estimated, the school intercepts and the country intercepts have statistically significant variance components. Therefore, average scores for students vary depending upon the school as well as the country. Additionally, the statistically significant variance components justify the use of multilevel modeling. Gender randomly varies at the school-level in all models and at the country-level in Model 1 only. In other words, the influence of gender on financial knowledge does vary by which school the student attends but in Models 2 and 3, it does not vary by country.

5.4.3 Comparison of Weighting Strategies with the Unrestricted Sample

To compare weighting strategies using the unrestricted samples, estimates from Table 5.6 (using both student- and school-level weights) are compared to estimates from Table 5.8 (using the student-level weight only). The main difference in the model estimates has to do with the findings in the gender gap. Model estimates from Table 5.6 report no gender gap, while model estimates from Table 5.8 report some presence of a small gender gap favoring men. Since estimates from Table 5.8 did not take into account the differing sample sizes in the number of schools, certain schools could be influencing the data, causing the presence of this gender gap. The other main difference is found when examining either the labor force participation rate for women (Model 2) or the overall labor force participation rate (Model 3). Table 5.8 reports statistically significant correlations between these labor force participation rates and the gender gap, while estimates from Table 5.6 do not report statistically significant estimates. While the most conservative estimates take into account both the student- and school-level weights, more work should be done to determine the best weighting strategy for subsequent analyses.

5.4.4 Restricted Model Estimates – Student- and School-Level Weights

Analyses conducted with the unrestricted sample are also conducted with the restricted sample using both student- and school-level weights. To justify the use of multilevel modeling, an unconditional model of student knowledge on the PISA 2012 Financial Literacy Assessment is built. Unconditional models seek to explain the amount of variance at each level without the use of any independent variables. In the unconditional model, 49% of the variance in student knowledge occurs at the student level, which implies that student characteristics can explain under half of the variance in scores. 50% of the variance in student knowledge occurs at the school level, and the remaining 1% of variance occurs at the country level of analysis. Due to the low amount of variance explained at the country level, proportions of variance explained at level 3 are not examined in subsequent analyses. The amount of variance at each level is different than in the unrestricted sample in a few ways. First, the majority of the variance occurs at the school level rather than at the student level. Second, less of the variance in scores occurs at the country level. As a result, the sizes of the effects reported are small and should be interpreted cautiously. Yet, the fact that most of the variance occurs at the school level justifies the use of multilevel modeling.

As with the unrestricted sample, three models examining the relationships between country-level variables, average student performance, and gender gap are examined. Results of the model estimates are presented in Table 5.10.

Table 5.10 Multilevel Regression Estimates of Predictors of Financial Knowledge, Fixed Effects, Restricted Sample, Country Analyses, Student- and School-Level Weights, PISA 2012

	Model 1	Model 2	Model 3
Fixed Effects			
Level 1			
Intercept	487.61**	491.69**	492.81**
	(8.26)	(7.85)	(7.50)
Male	0.88	0.34	2.64
	(5.44)	(11.08)	(10.11)
ESCS	28.22**	29.94*	29.87*
	(6.16)	(8.51)	(8.52)
Level 3 – Intercept-as-Outcome			
GDP		0.00	0.00
		(0.00)	(0.00)

Table 5.10 continued

OECD		1.95	1.23
		(21.45)	(21.17)
LFPRw		148.78	
		(94.20)	
LFPR			176.28
			(109.97)
Unemployment		118.88	121.79
		(200.95)	(208.36)
Level 3 – Gender Slope-as-Outcome			
GDP		0.00	0.00
		(0.00)	(0.00)
OECD		4.70	2.39
		(29.18)	(29.67)
LFPRw		-17.74	
		(127.48)	
LFPR			35.47
			(140.59)
Unemployment		251.25	263.97
		(264.52)	(281.38)
% of level-1 variance explained	0.67	0.67	0.67
% of level-2 variance explained	0.46	0.47	0.47

Note: **p<0.001; *p<0.01
Note: Standard error in parentheses.

Model 1 estimates student performance with *Male* and *ESCS* entered as grand-mean centered independent variables. As with the unrestricted sample, both the average student performance across the sample (intercept) and *ESCS* are positive and significant. The financial knowledge of the high school students in the sample was on average around 488 points. Students from higher socioeconomic backgrounds tended to have more financial knowledge. Surprisingly, no gender gap in financial knowledge is present despite the fact that analyses using the same sample in Chapter 4 found a significant gender gap in knowledge, whereby male students outscored female students. The difference in these analyses could be attributed to the estimation procedures used or to the weighting strategies used. In these analyses, HLM 7 software was used, while SAS® 9.2 was used in previous analyses. HLM 7 uses a different estimation procedure than SAS® 9.2, which could account for the different gender findings. SAS® 9.2 used restricted maximum likelihood estimation (REML) as the basis for estimation, and the Satterthwaite method is also used to account for the unbalanced design of students within schools and the complex covariance structures (Bell et al., 2013). HLM 7 also used REML, but estimation begins first with OLS estimates (Garson, 2013). Additionally, both student- and school-level weights are used in these analyses, which do influence the fixed effect coefficients.

Models 2 and 3 add country-level variables to examine the correlations between the indicators and average student performance as well as the correlations between the indicators and the gender gap in financial knowledge. Similar to the unrestricted sample, none of the country-level variables in either Model 2 or Model 3 are significantly correlated with the average performance of the students in the sample. Therefore, the economic conditions within a country did not seem to be related to student performance on the PISA 2012 Financial Literacy Assessment. In terms of the gender gap findings, country-level variables are once again not significantly correlated with the gender gap in financial knowledge. It could be argued that this is due to the lack of a gender gap in the sample. However, the lack of relationships between country-level variables and the gender gap in financial knowledge could also stem from the fact that students in the sample are too young to be affected by the economic conditions within their own country.

In terms of the amount of variance explained, the restricted sample paints a very different picture than the unrestricted sample. In Model 1, 67% of the student-level variance and 46% of the school-level variance is explained by the student-level variables of *ESCS* and *Gender*. Thus, Model 1 appears to fit the data well. However, when examining country-level variables, the percentage of variance explained at the student level stays the same in both Model 2 and Model 3. In terms of the school-level variance, the addition of country-level variables explains 47% of school-level variance. These analyses point to the fact that a student's socioeconomic status *(ESCS)* accounts for most of the variance in student financial knowledge, and country-level variables do not account for much variance in student knowledge. Additionally, the fixed effects estimates of country-level variables are limited in the size of their effects due to small standard errors and little additional variance explained.

Table 5.11 depicts the random effects, or variance components of the models estimated for the school-level intercept, the country-level intercept, and whether or not gender varied among schools and among countries.

Table 5.11 Multilevel Regression Estimates of Predictors of Financial Knowledge, Error Variance, Restricted Sample, Country Analyses, Student- and School-Level Weights, PISA 2012

	Model 1	Model 2	Model 3
Error Variance/Random Effects			
Level 2 (Residual)	1724.39	1724.76	1724.62
	(41.53)	(41.53)	(41.53)
Intercept (Level 1 & 2)	2917.61**	2912.81**	2913.14**
	(54.01)	(53.97)	(53.97)
Gender (Level 1 & 2)	15493.64**	15479.28**	15489.37**
	(124.47)	(124.42)	(124.46)
Intercept (Level 3)	403.66**	273.32**	257.62**
	(20.09)	(16.53)	(16.05)
Gender (Level 3)	117.16**	68.32**	70.96**
	(10.82)	(8.27)	(8.42)

Note: **p<0.001; *p<0.01
Note: Level-1 residual values do not report statistical significance.

Note: Standard deviation in parentheses.

The variance components in the restricted sample show that both average performance and gender vary among schools and countries. Both the school-level intercept and the country-level intercept are statistically significant in all models estimated, indicating that the average financial knowledge of students varies depending on the school they attend and/or the country in which they live. The variance components for gender are also statistically significant at both the school level and the country level. Gender does influence average performance by school and average performance by country, and the gender influence varies depending on the school and the country. The statistical significance of the variance components also indicates that random variance in general is present and that random effects should utilized in statistical analyses. Therefore, the use of multilevel modeling is justified.

5.4.5 Restricted Model Estimates – Student-Level Weight

Analyses using the restricted sample are also conducted using only the finalized student-level weight. Table 5.12 presents multilevel modeling estimates on the restricted sample using only the student-level finalized weight.

Table 5.12 Multilevel Regression Estimates of Predictors of Financial Knowledge, Fixed Effects, Restricted Sample, Country Analyses, Student-Level Weight, PISA 2012

	Model 1	Model 2	Model 3
Fixed Effects			
Level 1			
Intercept	502.36***	502.38***	502.42***
	(5.57)	(5.35)	(5.36)

Table 5.12 continued

Male	11.41*** (2.77)	11.99*** (2.24)	12.05*** (2.09)
ESCS	33.41*** (2.16)	33.30*** (2.18)	33.33*** (2.18)
Level 3 – Intercept-as-Outcome			
GDP		-0.0002 (0.0006)	-0.0002 (0.0006)
OECD		-2.00 (10.97)	-0.97 (11.43)
LFPRw		95.36 (83.17)	
LFPR			94.50 (92.49)
Unemployment		-47.33 (74.12)	-41.67 (72.72)
Level 3 – Gender Slope-as-Outcome			
GDP		0.0005 (0.0002)	0.0001 (0.0002)
OECD		-0.97 (8.13)	-0.50 (7.51)
LFPRw		64.84 (31.40)	
LFPR			88.05* (34.79)
Unemployment		66.82 (51.86)	77.38 (53.61)
% of level-1 variance explained	0.29	0.29	0.29
% of level-2 variance explained	0.44	0.44	0.43

Note: ***p<0.001; **p<0.01; *p<0.05
Note: Standard error in parentheses.

Model 1, the level-1 intercept, *Male*, and *ESCS* are positive and statistically significant. The statistically significant coefficient of 11.41 on *Male* indicates that being male is associated with an increase of 11.41 points. Therefore, a pronounced gender gap is present in this sample of students. Additionally, a student's socioeconomic status is also positively correlated with increases in demonstrated financial knowledge on the assessment.

As with previous estimations of Model 2, country-level variables are added to determine if they are correlated with average performance and/or the gender gap. While the level-1 intercept, *Male*, and *ESCS* remain positive and significantly correlated with student financial knowledge, none of the country-level variables in Model 2 are statistically significant. Model 3 also examines the relationship between average performance and country-level characteristics as well as the gender gap and country-level characteristics. The only statistically significant finding for country-level characteristics is the marginally significant coefficient on *LFPR.* In terms of the amount of variance explained, Model 1 explains 29% of the level-1 variance and 44% of the variance at level 2. Models 2 and 3 do not explain any additional variance, which indicates that model specification may be an issue. As with all of the country-level model estimates presented, the size of the effects are small and should be interpreted cautiously due to the small standard errors and small amounts of variance explained.

Table 5.13 shows the random effects, or variance components of the models estimated for the school-level intercept, the country-level intercept, and whether or not gender varied among schools and among countries.

Table 5.13 Multilevel Regression Estimates of Predictors of Financial Knowledge, Error Variance, Restricted Sample, Country Analyses, Student-Level Weight, PISA 2012

	Model 1	Model 2	Model 3
Error Variance/Random Effects			
Level 2 (Residual)	4598.78	4600.57	4599.53
	(67.81)	(67.83)	(67.82)
Intercept (Level 1 & 2)	1220.94***	1223.29***	1223.81***
	(34.94)	(34.98)	(34.98)
Gender (Level 1 & 2)	4123.55***	4115.40***	4110.53***
	(64.21)	(64.15)	(64.11)
Intercept (Level 3)	513.21***	458.46***	463.33***
	(22.65)	(21.41)	(21.52)
Gender (Level 3)	50.36**	13.62*	11.37
	(7.10)	(3.69)	(3.37)

Note: ***p<0.001; **p<0.01; *p<0.05
Note: Level-1 residual values do not report statistical significance.
Note: Standard deviation in parentheses.

Table 5.13 indicates that average performance varies by both school and by country. This is indicated by the statistically significant variance components of intercept (level 1 & 2) and intercept (level 3). Additionally, the finding justifies the use of multilevel modeling, as average performance can depend upon the school and the country examined. Gender does vary by both school and by country in Models 1 and 2. In Model 3, gender only varies by school.

5.4.6 Comparison of Weighting Strategies Using the Restricted Sample

To compare weighting strategies with the unrestricted samples, estimates from Table 5.10 (using both student- and school-level weights) are compared to estimates from Table 5.12 (using the student-level weight only). The main difference in the estimates for the two different weighting schemes lies in the coefficient on *Male.* Estimates from Table 5.10 find no statistically significant coefficients on the *Male* variable, while estimates from all models in Table 5.12 show that *Male* is positive and highly significant. It can be concluded that using both student- and school-level weights in the restricted sample of students produces no gender gap in achievement, while using only the student-level weight does show a gender gap favoring male students.[12] Again, the difference in these estimates is likely due to the differing influence of particular schools. When using the school-level weight, model estimates account for the different number of schools within countries, whereas not using the school-level weight implies that certain schools could exhibit more influence over model estimates.

5.5 Discussion

Past research has shown a persistent gender gap in the financial knowledge of high school-aged students (Atkinson & Messy, 2012; Lusardi et al., 2010; Varcoe et al., 2005). In attempts to explain the gender gap in financial knowledge, some studies have explored links between country-level variables and financial knowledge (Atkinson & Messy, 2012; Jappelli, 2010; LoPrete, 2013; Lusardi & Mitchell, 2011). This chapter adds to the growing body of literature regarding the gender gap in financial knowledge through examining the relationships between macroeconomic indicators and student financial knowledge. In other words, the goal of this chapter is to determine whether or not economic conditions within the student’s home country may influence the student’s financial knowledge and whether or not these same conditions may influence the gender gap in financial knowledge. For the sample of students participating in the PISA 2012 Financial Literacy Assessment, depending on

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[12] Finding a gender gap with only the student-level weight is consistent with findings from Chapter 4.

the weighting strategy used, there may or may not be a gender gap in financial knowledge found in the data. Analyses using both student- and school-level weights to account for differing sample sizes find no gender gap present in both the unrestricted and the restricted samples. These results are similar to those of Walstad et al. (2010), and Hill and Asarta (2016), who found no gender differences in samples of high school students from the United States. The findings also contradict the findings from countries such as Germany, Japan, New Zealand, and the United States, where gender gaps in financial knowledge have been reported (Becchetti et al., 2013; Jang et al., 2014; Lührmann et al., 2012; Lusardi et al., 2010; Varcoe et al., 2005). Most of the research examining gender gaps in financial knowledge were for individual countries only, and thus direct comparisons to this chapter are not easily made.

However, when examining estimates using only the student-level weight, a gender gap favoring males is present. Yet, the mixed findings regarding the gender gap are also consistent with a great deal of research. At the adult level using international samples, the research on gender gaps in financial knowledge shows mixed results; some studies point to males having greater financial knowledge (Falahati & Paim, 2011; Hung et al., 2012; OECD, 2013b), while others show that women have greater financial knowledge (Atkinson & Messy, 2012). Since the dataset represents the first international comparison of the financial knowledge of high school students, the work contributes to the field despite the fact that gender differences in financial knowledge may or may not be present. In order to determine whether or not the finding, or lack thereof, accurately depicts what is occurring throughout the world, more internationally comparative assessments need to be administered and analyzed. Weighting schemes should also be clearly defined in any subsequent analyses.

In terms of overall student performance, none of the country-level variables examined are correlated with average student performance in estimates for both weighting schemes. Variables examined include GDP per capita, whether the student's country was a member of the OECD, the 2011 unemployment rate, the 2011 labor force participation rate, and the 2011 labor force participation rate for women. Findings here are similar to those of past research, which also found no statistical relationship between financial knowledge and GDP as well as between financial knowledge and unemployment (Behrman et al., 2010; Jappelli & Padula, 2013; Lo Prete, 2013). It is difficult to determine why macroeconomic indicators are not correlated with financial knowledge of the students in the PISA sample. Many students are too young to work, thus affecting their role in the economy, which may have contributed to the findings. However, because the sample includes many different countries, I cannot comment with certainty. Given that each country has different economic and cultural landscapes, it is difficult to control for a student's economic and cultural surroundings within the student's home country.

Similar to overall student performance, the gender gap in achievement is not correlated with the country-level variables included in analyses using both the student- and school-level weights. There are a few possible reasons for the lack of a relationship present in the findings. First, since no gender gap was found in analyses using both weights before adding the country-level variables, there was no gender gap to explain. Secondly, there could have been a misspecification error in the country-level variables used. More specifically, incorrect regressors could have been examined. It may be the case that some country-level variables are related to student financial knowledge, but the correct regressors were not included in the model. Efforts to avoid misspecification errors were taken early in the analysis process, but there are always possible contributing factors that could have been overlooked. The proportion of variance explained also pointed to the fact that student-level characteristics such as ESCS and Gender explained a great deal of variance at all levels of analysis, but country-level variance did little to explain what is happening in the data. This was true for both the unrestricted and restricted samples. In model estimates using only the student-level weight, LFPRw and LFPR could be associated with the gender gap, but the coefficients were only marginally significant and more work should be conducted to determine the true correlations between these variables. The interpretations provided in this chapter discuss the coefficients of the fixed effects and possible implications, though the estimates presented are limited by both small standard errors and low amounts of variance explained.

While results did not indicate significant relationships between country-level variables and either average student financial knowledge or the gender gap in financial knowledge, this chapter provides a number of lessons to be learned. First, the PISA 2012 Financial Literacy Assessment data should be analyzed using multilevel modeling procedures. Through the examinations of the variance in student financial knowledge at each level of analysis, it is clear that the data is hierarchical in nature. Thus, the most accurate and appropriate analyses account for the hierarchy of the data. Further examination of methodological approaches and model specifications will be undertaken extensively in a subsequent chapter to further emphasize the importance of using multilevel modeling. The results presented in this chapter are also limited by the relatively small number of groups for analysis at the country level.

Second, whether or not a gender gap is present across the sample of students depends on the weighting strategy and sample used. Previous literature regarding the gender gap in financial knowledge reported mixed findings: some international samples reported a pronounced gender gap between male and female students (Lührmann et al., 2012; Cameron et al., 2014), while other samples found no difference (Sohn, Joo, Grable, Lee, & Kim, 2012). The research here mimics previous findings. There is a lack of a gender gap in financial knowledge for the unrestricted sample using both student- and school-level weights; yet, analyses conducted using the restricted sample and only the student-level weight do find gender differences between male and female students. The research presented in this chapter focuses on the gender gap in knowledge across the entire sample of countries rather than on the gap in knowledge within each of the countries. According to the OECD (2014a), gender differences in financial knowledge are reported within specific countries in the PISA 2012 Financial Literacy Assessment data. Given this fact, further investigations of a gender gap in financial knowledge should be examined within specific countries of interest.

Third, across the sample of students, country-level variables are not correlated with either student performance or with the gender gap in achievement. Previous research also found no relationships between country-level variables and financial knowledge (Behrman et al., 2010; Jappelli, 2010). Most of the countries in the sample were developed countries, which could influence the relationships between country-level variables and financial knowledge. As Klapper et al. (2015) found, individuals from developing countries tended to have less financial knowledge than those from developed countries. Perhaps an expanded sample of students from developed and developing countries would be best suited to answering questions about the influence of country-level variables. The sample of countries from the PISA 2012 dataset was rather homogenous, in that many were OECD member countries with relatively high GDP per capita. Adding more diverse countries would help to more accurately measure country effects.

Lastly, a lesson about weighted multilevel modeling can be learned here. When examining two different weighting schemes, one using both student- and school-level weights to account for differing student and school sample sizes, and another using only the student-level weight, the models produce differing estimates for both the restricted and unrestricted sample. The main difference in these weighting schemes seems to lie in whether or not models detect the presence of a gender gap in financial knowledge favoring males. Using both weights finds no gender gap present, while the use of only the student-level weight does show a gender gap favoring male students. More work should be conducted to determine the correct weighting scheme with this data for future analyses.

The findings in this chapter contribute to the growing literature on the financial knowledge of high school students and on international comparisons of financial knowledge. Through the use of multilevel modeling, analyses examined relationships between country-level variables and the financial knowledge of high school students using the PISA 2012 Financial Literacy Assessment data. To date, little research has used an internationally comparative dataset of this magnitude. In addition, the gender gap in financial knowledge is examined in order to determine if country-level variables are related to the gap in knowledge. In the PISA 2012 Financial Literacy Assessment sample, it is unclear whether or not a gender gap is present, and country-level variables are not related to the gender gap. Analyses justified the use of multilevel modeling procedures, as a significant amount of variance occurred beyond the student level. Results did not show relationships between country-level variables and either student financial knowledge or the gender gap in financial knowledge, across the sample of students, indicating that country-level variables may not contribute to a student's understanding of financial concepts. Future research should examine different macroeconomic variables, expanded samples of students from different countries to not only examine more countries but to also increase the country-level sample size, and samples of students from different time periods to determine whether or not a country's characteristics influence student financial knowledge.

Chapter 6

METHODOLOGICAL COMPARISON OF MULTILEVEL MODELING AND REGRESSION ANALYSES

In this chapter, I compare multilevel modeling results to regression analyses results using the PISA 2012 Financial Literacy Assessment in order to draw conclusions about the most appropriate methodological approach to analyze the data. Guided by the research questions asked in Chapter 1, this chapter answers the following research questions presented in Section 1.2.1:

4. In the context of the PISA 2012 Financial Literacy Assessment, are multilevel models or regression analyses better suited for analyzing the data and answering the research questions presented above? Which methodological approach should be used when examining the PISA 2012 data, and why?

Section 6.1 provides background information for the chapter. Next, sections 6.2 and 6.3 discuss the theoretical backgrounds of multilevel modeling and regression analysis, respectively. Then, section 6.4 compares multilevel modeling and regression analysis in a theoretical context. Section 6.5 next discusses the statistical methodology for the chapter. Results are found in sections 6.6 – 6.8. Section 6.6 contains previously estimated multilevel models including parental characteristics found in Chapter 4, as well as newly estimated regression analyses. Multilevel modeling results and regression results are also compared in section 6.6. Section 6.7 contains previously estimated multilevel modeling with country-level variables using the unrestricted sample from Chapter 5, as well as newly estimated regression analyses. As with section 6.6, section 6.7 also compares multilevel modeling results and regression results. Section 6.8 mimics section 6.7, except analyses are conducted for the restricted sample. Finally, section 6.9 provides a discussion of the findings, implications, and limitations of Chapter 6.

6.1 Introduction

One way in which educational research and economic research vary is in the preferred estimation technique used for predicting student achievement. Educational research tends to use multilevel models, or hierarchical linear models, with random effects to address the nested structure of the data (Garson, 2013; Raudenbush & Bryk, 2002), while economic research tends to use regression analysis (Greene, 2012; Gujarati & Porter, 2009). In multilevel modeling, Bayesian estimation is used to produce an estimate that is a combination of prior information and the likelihood of the data. This procedure creates “shrinkage” estimates, which are estimates of means influenced by other groups in the data (Raudenbush & Bryk, 2002). With regression analysis, ordinary least squares (OLS) estimators are often used to minimize the error of each data point (Greene, 2012; Guajarati & Porter, 2009). Despite the differences in methodological approach, the two types of modeling have been used with educational data.

To date, it has been at the discretion of the researcher to determine which methodological approach to use when examining educational data. Using the PISA 2012 Financial Literacy Assessment data, this chapter compares estimates from multilevel models to those from regression models to determine the appropriate methodological approach to analyze the data. The PISA 2012 data set represents an internationally comparative, hierarchical data set, leading to issues of dependence and heteroscedasticity that typical regression analyses may not be able to handle. The challenging part of the methodological comparison is that, to date, there is no conclusive statistical test that can provide the correct answer as to which methodology to use with hierarchical data. Previous comparisons of multilevel modeling and regression analyses, however, have deemed multilevel modeling the more appropriate approach to use with hierarchical data (Osborne, 2000; Steenbergen & Jones, 2002). To prove whether or not previous research was correct, multilevel modeling results from Chapter 4 and Chapter 5 are used to compare to newly estimated regression models using the same subsamples and variables. Comparisons are made based on model estimates, model diagnostics, and variance structures. The methodological comparison made in this chapter will not only help in the context of this research but will hopefully provide guidance to future researchers confronted with similar methodological considerations.

6.2 Multilevel Modeling Approach

Multilevel modeling has become a popular estimation method in educational research due to the nested nature of educational data. Multilevel modeling is often called hierarchical linear modeling (HLM) in educational research and random coefficient regression models in economics (Garson, 2013; Raudenbush & Bryk, 2002). The PISA 2012 Financial Literacy Assessment data has a natural hierarchy, where students exist within schools, and schools exist within countries, giving the data a three-level hierarchy. Due to the nested nature of the PISA 2012 dataset, multilevel models are used to the examine relationships between a student's gender, parental characteristics, country-level variables, and student financial knowledge. Multilevel models are also used to account for the dependence of observations within nested data structures and allow for the examination of cross-level interactions.

Multilevel modeling has been applied to many types of research across a variety of fields, though it appears that each field of research calls this type of modeling something different. Raudenbush & Bryk (2002), for example, note that sociology tends to use the terms multilevel linear models. Biometrics uses mixed-effects models, and economic research refers to these models as random-coefficient models. The term hierarchical linear models was originally developed for use in organizational research by Lindley and Smith (1972) who were among the first researchers to estimate models with nested data using Bayesian estimation techniques (Raudenbush & Bryk, 2002). It was not until the 1970s and 1980s that multilevel models could be correctly estimated due to the advent of new estimation methods (Draper, 1995). Since then, many applications of multilevel modeling have become very popular. In fact, educational research has since adopted the term HLM as its own. For the purpose of my research, which crosses the disciplines of economics and education, models using this type of estimation will henceforth be referred to as multilevel models. Despite the differing nomenclature, the models estimated across the different disciplines share certain basic characteristics. First, multilevel models account for the nested nature of certain datasets and the corresponding dependence of observations. Secondly, multilevel models use Bayesian estimation techniques. Also, multilevel models allow for the examination of fixed effects as well as random effects within the different levels of hierarchy. Finally, many types of multilevel models exist to answer different kinds of research questions.

By definition, nested data occurs when individual observations exist within different organizational structures. In education, the structure tends to be students “existing” within classrooms, within schools, and/or within school districts (Gorard, 2003; Huta, 2014; Osborne, 2000; Raudenbush & Bryk, 2002). In the case of the PISA 2012 data, students "exist" within schools, and schools "exist" within countries. In other words, students are nested within schools, which are then nested within countries. Due to the nested structure of this data, individual observations will exhibit some homogeneity across subjects. For example, student "a" from school "b" in country "c" will be more similar to his or her peers within school "b" and country "c." Therefore, students within the same school and even within the same country will share many similar characteristics, causing the observations to no longer remain independent of one another (Gorard, 2003). Nested data violates the assumption in ordinary least squares that the correlation between any two observations, or cases, must be zero. Multilevel modeling allows for analyses to be conducted despite the fact that the assumption of independent observations is violated (Gorard, 2003). Since many basic regression estimation techniques require the assumption of the independence of observations, methods such as linear regression are inadequate when estimating models using nested data.

Multilevel models use maximum likelihood with empirical Bayesian techniques to estimate parameters. Maximum likelihood seeks to maximize the likelihood function, or to select values based only on the data that is given (Greene, 2012). On the other hand, Bayesian estimation is based on the idea that more information exists beyond the sample data. Estimates produced as a result of Bayesian estimation are a combination of both prior information and the data likelihood. Using this idea, empirical Bayesian estimate parameters are found as a weighted average of both the group mean and the overall mean. The types of estimates produced are sometimes referred to as shrinkage estimates, as they are "shrunk" to the group means surrounding the data (Raudenbush & Bryk, 2002). One advantage of this approach is that groups with smaller sample sizes can borrow strength from groups with larger samples. In fact, the use of shrinkage estimates is often referred to as "borrowing strength" as other group means can directly impact data points in other groups. Multilevel models cluster data using maximum likelihood estimates and subsequently borrow strength from other data points and from other clusters/groups (Clarke et al., 2010; Gujarati & Porter, 2009; Raudenbush & Bryk, 2002). Due to the concept of borrowing strength, multilevel models can also explore links between the different levels, rather than just exploring the entire sample while controlling for a specific level (Michaelowa, 2001). Multilevel models are not far removed from ordinary least squares (OLS) estimation except that multilevel models account for the hierarchical nature of the data and the shared variance across observations rather than assuming non-clustered data and constant variance (Steenbergen & Jones, 2002; Woltman et al., 2012).

Multilevel models can include both fixed effects and random effects to allow for shrunken and more precise estimates, as well as differing results among the different levels of analysis (Clarke et al., 2010). Many different types of multilevel models can be estimated. The most basic type of model is known as a fixed-effect model, which estimates relationships with the intercept as fixed effects. Fixed-effect models are similar to OLS regression models except that these types of models account of the nested structure of the data. In contrast to fixed-effect models, random-effect models include random factors that influence the covariance structure rather than the intercept. The third type of multilevel models is a mixed model, which combines fixed effects and random effects into one model. Any predictor at any level can be included as a fixed effect, while random effects are shown as slopes of variables at lower levels (Garson, 2013).

By definition, hierarchical linear models look at “differences between groups (ex., schools) in relation to differences within groups (ex., among students within schools)” (Garson, 2013, p. 8). Within the context of HLM, there are different types of models that can be estimated. The first type of model is a one-way ANOVA with random effects, more commonly referred to as a null model or an unconditional model (Raudenbush & Bryk, 2002). The simplest type of modeling in an HLM context, this type of random intercept model aims to predict the dependent variable with only a random effect of the higher level’s grouping terms and no other predictors at any level of analysis (Garson, 2013; Raudenbush & Bryk, 2002). Unconditional models are used to calculate the amount of variance in the outcome variable that exists at each level of analysis, and unconditional models serve as a baseline model for all subsequent models (Garson, 2013). The second type of HLM is known as a means-as-outcomes regression model or a random intercept regression model. In this type of modeling, the means across the many groups are predicted by random group characteristics (Garson, 2013; Raudenbush & Bryk, 2002). A third type of model is a one-way ANCOVA with random effects model, which blends the ANOVA and regression approaches. This type of model predicts a level-1 intercept as a random effect of the level-2 grouping variable with no level-2 predictors (Garson, 2013). Random coefficients regression models are also very common, as the level-1 intercept is predicted by at least one level and by one covariate. In this type of modeling, each group at any level higher than level 1 is assumed to have its own intercept and slope term that predict the dependent variable. Simplistically, this type of model is similar to fitting a linear regression for each group represented in the nested data (Garson, 2013; Raudenbush & Bryk, 2002). The final type of model that can be estimated within the context of HLM is known as intercepts-and-slopes-as-outcomes modeling. When estimating these types of models, the variability of both the intercepts and slopes can be estimated across the higher levels of grouping. Thus, for a two-level model, not only is the level-1 intercept estimated as a random factor by the grouping variable at level 2 but it can also be estimated by other level-2 variables (Garson, 2013; Raudenbush & Bryk, 2002). Figure 6.1 on the following page depicts the different types of models using an example of a two-level educational model with a specific dataset.

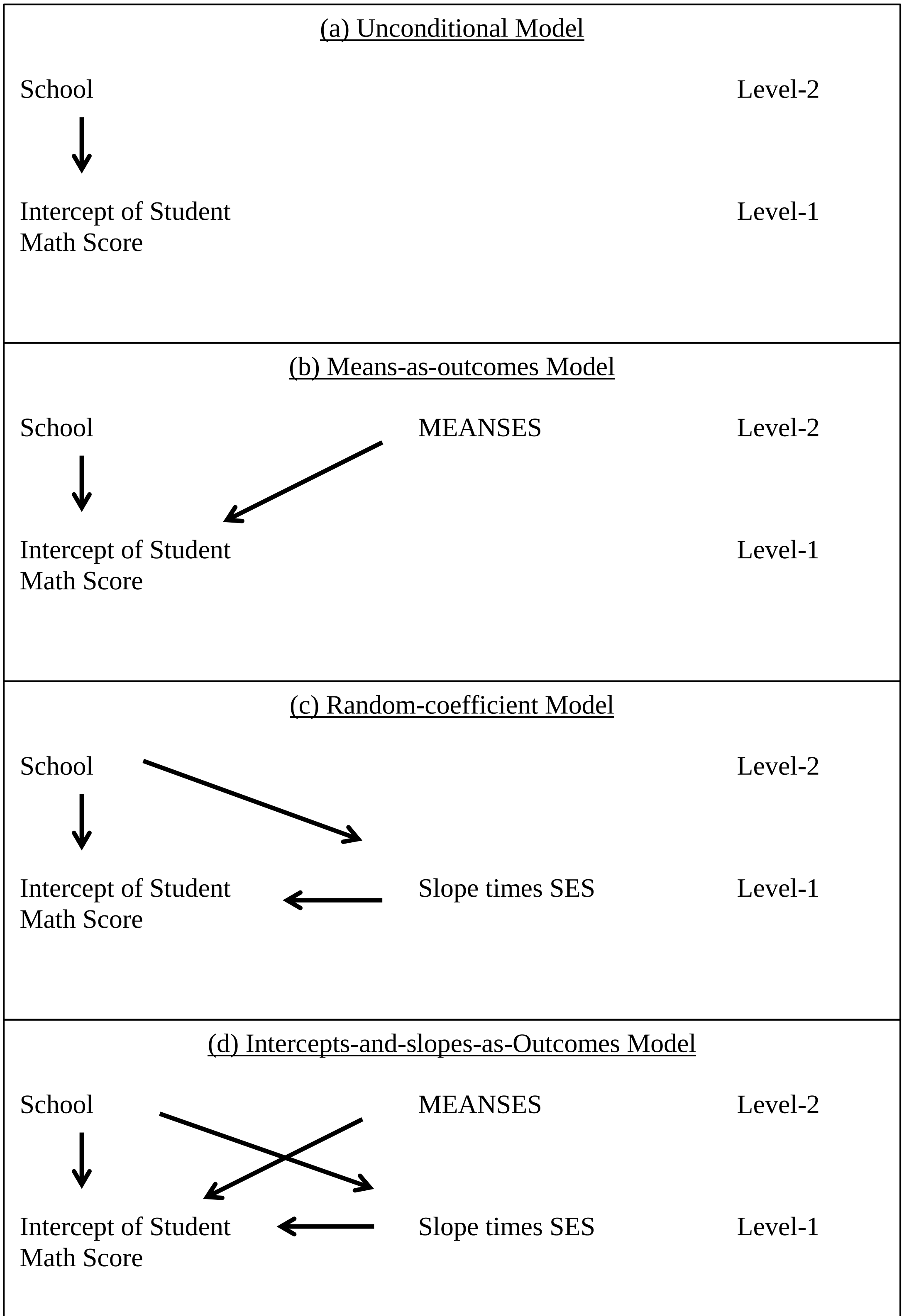
(a) Unconditional Model
School
Level-2
Intercept of Student Math Score
Level-1
(b) Means-as-outcomes Model
School
MEANSES
Level-2
Intercept of Student Math Score
Level-1
(c) Random-coefficient Model
School
Level-2
Intercept of Student Math Score
Slope times SES
Level-1
(d) Intercepts-and-slopes-as-Outcomes Model
School
MEANSES
Level-2
Intercept of Student Math Score
Slope times SES
Level-1

Figure 6.1 Different Types of Two-Level Hierarchical Linear Models

Note: This figure is adapted from Raudenbush & Bryk (2002) and Garson (2013).

Figure 6.1 shows an example of four typical types of hierarchical linear models as used by Raudenbush & Bryk (2002) and Garson (2013). To give the models context, assume that the dataset being used is the 1982 High School & Beyond dataset (HSB) containing information on 7,185 students from 160 schools in the United States. Two-level models can be built with two variables at each level of analysis. At the student level, there is an outcome variable of a student's standardized math achievement as well as the student's socioeconomic status (SES). At the school level, there is a variable indicating whether the school is a public school (=0) or a private school (=1) called SECTOR. The other school-level variable is MEANSES, or the average socioeconomic status within a given school (Raudenbush & Bryk, 2002). Figure 6.1 describes four different hierarchical linear models that could be applied to the HSB data. Panel (a) depicts an unconditional model, where the intercept of the student's math score is predicted by the school grouping variable without any other independent variables. Panel (b) shows a means-as-outcomes model, where school means are predicted for each school in addition to the overall student intercept. Random effects are present here in the form of the school means, and MEANSES is used as a predictor of the school slope. Panel (c) represents a random-coefficient model, where the student intercept, or average student performance, is predicted by a student-level variable such as SES. Random-coefficient models use fixed effects while allowing the school to vary. Finally, panel (d) displays an intercepts-and-slopes-as-outcomes model. Intercepts-and-slopes-as-outcomes models combine the models in panel (b) and panel (c). These models use both fixed and random effects to estimate relationships between student-level predictors and the student intercept as well as to estimate school means as predicted by school-level variables such as MEANSES. As Figure 6.1 illustrates, all four types of models can be utilized in an HLM framework depending on the variables used and research questions asked.

6.3 Regression Analysis Approach

Large-scale data analysis in economics and other fields is typically done using regression analysis. Educational data is no exception. In light of the fact that analyzing the PISA 2012 dataset falls under the realm of large-scale data analysis, regression estimation procedures are also used to examine student financial knowledge. Given that the PISA 2012 dataset constitutes a nested or hierarchical, international dataset, some changes must be made to the standard regression estimation procedures. Specifically, weighted, cluster-robust regression models are estimated to account for the nested data structure and unequal sample sizes.

The standard regression method of estimation used to model how certain aspects explain an outcome is through the use of ordinary least squares (OLS) or the classic linear regression model (CLRM). Using classic linear regression, observations are fitted to a linear model that seeks to minimize the amount of error between the observation and the estimated data point (Greene, 2012; Gujarati & Porter, 2009). OLS has been effective in a variety of economic applications, most often with fixed effects in the context of both cross-sectional and panel data (Clarke et al., 2010).

The most commonly used statistical analysis in economics, ordinary least squares (OLS), has a variety of features that make it unique when applying to certain data. Named for the type of estimators and the least-squares principles, the idea behind the estimates is to create one fitted line through the data by minimizing the distance (or error) between a data point and the sample regression line (Gujarati & Porter, 2009). In order to estimate OLS estimators in classical linear regression modeling (CLRM), a series of assumptions must be made. A full list and discussion of these assumptions can be found in Gujarati and Porter (2009). For the purpose of comparing regression analyses to multilevel modeling, the focus here is on a few of the CLRM assumptions. First, the independent variables, or fixed regressors, are assumed to be independent or not correlated with the error term. Another assumption that must be made is that of homoscedasticity, or constant variance of the error term. This assumption implies that the error of each observation must be equally spread. When this assumption is violated, the data is said to have heteroscedasticity, wherein unequal variance exists (Gujarati & Porter, 2009). A fixed effect is a statistical model that is typically used in linear regression and/or ANOVA (Newsom, 2015). Fixed-effect regression models, often used with panel data, allow for group effects to be measured as long as each group's intercept does not change over time (Gujarati & Porter, 2009).

6.3.1 Regression Analysis with Nested Data

Due to the unique characteristics of international datasets and the nested nature of educational data, a few changes to a simple linear regression must be made. Nested data violates two of the main assumptions underlying a typical classical linear regression model and the OLS estimation process. First, OLS requires that the data is homoscedastic, or the data has equal variance. In other words, the error term needs to be the same for every value of x in order to minimize the error term across all of the data used. With nested data, however, error terms commonly have multiple components, one for each level or cluster (Moulton, 1986). Furthermore, considering that the PISA 2012 data is nested, the data shows dependence within clusters, thus causing heteroscedasticity, or unequal variance (Greene, 2012; Gujarati & Porter, 2009).

Nested data can also lead to smaller standard errors (Ammermüller et al., 2005). The method commonly used to correct for the problem of smaller or underestimated standard error is cluster-robust linear regression (CRLR). Cluster-robust linear regression allows for the dependence of individual observations within the given primary sampling unit, as long as there is independence across the different primary sampling units (Ammermuller et al., 2005). In this case, the primary sampling units are schools, which have been typically used with PISA data using educational production functions (Dronkers & Robert, 2008; Fuchs & Woessmann, 2004; Schütz, 2009). Cluster-robust estimators are used to correctly analyze the data. More specifically, White's heteroscedasticity-consistent estimators and robust standard errors are used to correct for heteroscedasticity (White, 1980). Using White's corrections should yield higher standard errors and smaller t-values with very little change to the parameters themselves (Gujarati & Porter, 2009; Schütz, 2009).

What is unclear, however, is if there is true independence across the primary sampling units. Schools within specific countries were chosen at random within a country in order to establish independence. However, schools were allowed to self-select out of the assessment, thus violating the idea of school independence. Countries chosen for the analysis were also not randomly chosen, violating some country-level independence (OECD, 2014a). To test whether there is true independence in the data, cluster robust linear regression models are examined as well as multilevel models.

Estimates from these two methodological approaches will yield potential answers to the question of independence of individual observations within the data.

The second issue within the PISA 2012 Financial Literacy Assessment data is the differing sample sizes both within and among countries. Each country has a different number of schools represented and thus a different number of students represented. Because there are different probabilities of schools and students being chosen in the sampled countries, an overrepresentation of certain individuals in the sample could be possible (Deaton, 1997). To correct for overrepresentation in subsequent analyses, the OCED included sample weights for students, schools, and countries in the PISA 2012 data (OECD, 2014a). For the purpose of the analyses in this dissertation, sample weights are used to ensure that analyses accurately represent the target population of 15-year-olds in the sampled countries. Thus, weighted clustered-robust linear regressions (WCRLR) are estimated (Deaton, 1997; Dumouchel & Duncan, 1983; Pfeffermann, 1993; Wooldridge, 2001). Analyses sought to explore relationships between the financial knowledge of students as measured by the PISA 2012 Financial Literacy Assessment and individual characteristics, parental characteristics, and country-level characteristics. The data used was cross-sectional in nature, having one time point for each student represented in the sample. Subsequent regression analyses of the PISA 2012 Financial Literacy Assessment utilize weighted, cluster-robust regression models to account for the issues that arise within the nested dataset and the differing sample sizes within schools and within countries.

6.4 Comparing Multilevel Models and Regression Analyses

Both multilevel models and regression analyses are utilized in this chapter in order to build a comparison of the two statistical methodologies. The methodologies and subsequent models are compared on the following features: the ability to handle nested data; the variance and error terms; the handling of both fixed and random effects; and the handling of cross-level interaction terms. In this section, these aspects of regression analyses are first examined followed by how multilevel modeling would handle these issues. In comparing these aspects, it appears as though there are more advantages to using multilevel modeling with educational data as opposed to using regression analyses.

6.4.1 Nested Data

Nested, or hierarchical data leads to estimation issues in many statistical analyses. For example, when using regression estimation with hierarchical data, Type I error is commonly found. Type I error in statistics is defined as an incorrect rejection of the null hypothesis (Greene, 2012); in other words, Type I error leads to many false positive results, such as finding a statistically significant result in regression analysis that is not actually significant. The reason for the increased probability of Type I error when using OLS regression analyses with nested data is due to the number of observations. With linear regression estimation, each data point is treated as if it is independent of all other data points. When the data is nested, however, there are inherent similarities within individual observations, especially if the observations are from the same group. Also contributing to the increased probability of Type I error are the smaller standard errors estimated when using regression analysis on nested data. The misestimation of standard errors with OLS regression analyses will increase the probability of finding statistical relationships when they do not exist (Garson, 2013). Regression analyses without proper statistical correction on nested data will hypothetically cause Type I error.

As previously mentioned, multilevel modeling is designed to be used with hierarchical or nested data, and thus can handle many of the issues that could arise within this type of data (Gorard, 2003; Huta, 2014; Osborne, 2000; Raudenbush & Bryk, 2002). Some academics have even gone as far as to argue that not using multilevel modeling with nested data will always lead to Type I error (Steenbergen & Jones, 2002).

6.4.2 Variance and Error Terms

As previously mentioned, nested data also exhibits some properties that violate the underlying assumptions of OLS regression analysis. Ordinary least squares regression requires that the data have equal variance, or be homoscedastic. The error terms need to be exactly the same for each individual observation in order to correctly estimate the OLS regressors. Ordinary least squares regression requires that the data is homoscedastic, or that the data, and error terms, have equal variance (Greene, 2012). Therefore, only one error term is modeled within the context of linear regression models. Often with nested data, this is not the case, and there is heteroscedasticity present when estimating regression models (Garson, 2013; Osborne, 2000). Therefore, regression analyses can correct for the presence of heteroscedasticity by using cluster-robust estimators, or White's heteroscedasticity-consistent estimators with robust standard errors (White, 1980). This processes leads to higher standard errors and smaller t-values with no change to the parameters themselves (Gujarati & Porter, 2009; Schütz, 2009). In essence, the cluster-robust correction allows for equal variance while still maintaining the one error term in the data.

Multilevel modeling accounts for the fact that nested data by nature exhibits heteroscedasticity, as observations belonging to the same group are inherently more similar than different. Multilevel modeling assumes observations will be dependent and the model accounts for this with the use of multiple error terms. The error terms that exist within multilevel models have multiple components, one for each level or cluster (Moulton, 1986; Raudenbush & Bryk, 2002). Often, educational research justifies the use of multilevel models through calculating the variance at the various levels of hierarchy in the data. More specifically, multilevel models make use of a statistical term known as the intraclass correlation, or ICC. One way to interpret an ICC is as the proportion of variance between the levels or clusters (Raudenbush & Bryk, 2002). In a three-level model, ICCs allow a researcher to determine the amount of variance in the dependent variable at level1, level 2, and level 3. In the case of the PISA 2012 data, ICC calculations allow one to see the amount of variance in student knowledge at the student level, at the school level, and at the country level. For any three-level multilevel model, an ICC for level 2 is calculated using the following formula:

$$\frac{\tau_\pi}{\sigma^2 + \tau_\pi + \tau_\beta}$$

where τ_π represents the variance components of the level-2 units, or the school units. σ^2 represents the variability of the level-1 units in the outcome.
and τ_β represents the variance components of the level-3 units, or the countries.

An ICC for level 3 is calculated using the following formula:

$$\frac{\tau_\beta}{\sigma^2 + \tau_\pi + \tau_\beta}$$

The ICC statistics are calculated using an unconditional model, where no independent variables are entered into the model to explain the dependent variable. An unconditional model is the equivalent of an ANOVA with random effects for groups.

In educational research using multilevel models, if there is significant variance at level 2 or level 3, then the use of multilevel models is justified (Raudenbush & Bryk, 2002; Osborne, 2000). Yet, no threshold exists as to what is defined as significant variance. Goldstein (1997) argued that with small ICCs, OLS and multilevel models yield similar results but different standard errors. This is especially true for small sample sizes. In regression analysis, the variance at each level cannot be determined. What is commonly reported, however, is the proportion of the variance explained by the model, or the r-squared value (Gujarati & Porter, 2009). This measure, however, is not quite equivalent to the variance component at each level of analysis. An r-squared value is analogous to the level-1 variance or ICC in multilevel modeling, but the r-squared does not examine the variance at any higher levels.

6.4.3 Fixed and Random Effects

Another notable difference between multilevel models and regression analysis is in the modeling of fixed effects and random effects. Ordinary least squares regression models with fixed effects assume that error terms and independent variables are correlated, whereas random effects models assume that error terms and independent variables are not correlated. In random effect models, it is also assumed that the error terms are randomly drawn from a much larger population (Gujarati & Porter, 2009). While multilevel models allow for variables to vary randomly, this is rare in regression analyses except for in panel data analysis. Garson (2013) noted that OLS regression treats estimated coefficients as fixed constants. When using OLS in a fixed-effect analysis, the inferences drawn can only be about the pool of observations given. In contrast, a random effect analyses can draw larger conclusions about that entire population from which the sample was drawn (Newsom, 2015). While fixed effects create dummy variables based on the group of an observation, random effects are used when the effect of a group is believed to have influence over a dependent variable (Klawitter, 2012; Newsom, 2015). In econometrics, random-effects models are used in panel data analyses, where data is both cross-section and time-series (Greene, 2012),

In determining whether to use random effects, fixed effects, or both, it is unclear exactly how to go about determining which is most appropriate for the PISA 2012 data, which is cross-sectional. For panel data, the choice is relatively clear. Figure 6.2 from Dougherty (2011) (as cited in Klawitter, 2012) demonstrates how one can go about choosing whether or not to use fixed-effects or random-effects regression models when answering research questions.

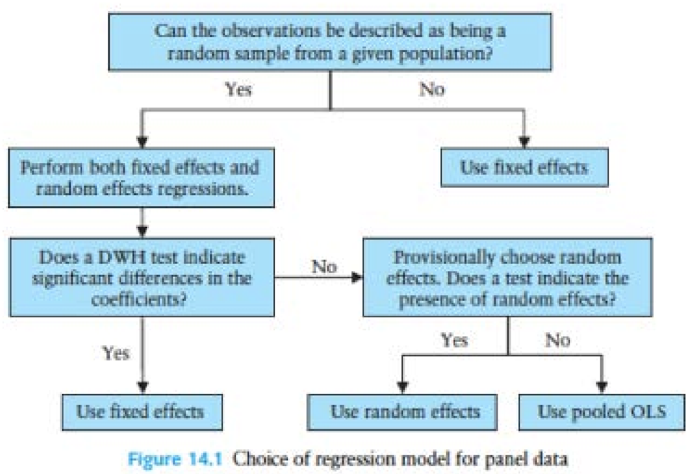

Figure 6.2 Choosing Fixed or Random Effects Flow Chart

Note: Adapted from Dougherty (2011) (as cited in Klawitter, 2012).

The figure shows one way to decide which type of modeling is appropriate for the data determined by whether or not the sample is randomly drawn from a given population as well as whether or not a Durbin-Wu Test or Hausman Specification Test indicates the presence of random effects (Greene, 2012). However, Figure 6.2 assumes the presence of panel data. In the case of the research in this dissertation, the data is cross-sectional, nested data. Outside of the use of panel data, there is no clear way of determining whether or not to use fixed-effect models or random-effect models in the context of regression analyses.

Multilevel modeling in fields such as educational research is used on any data where observations are nested and not just with panel data. Moreover, in the context of multilevel modeling, fixed effects examine the impacts of variables that influence the intercept, whereas random effects examine variables that influence the covariance structure of the data (Garson, 2013). It is much simpler to include both fixed and random effects in a multilevel modeling framework than in regression analyses.

6.4.4 Cross-Level Interactions

Lastly, there is a difference in how the two types of models look at cross-level interactions. In OLS regression, interaction terms examine the relationships between two independent variables in the regression model and how they potentially influence the dependent variable (Greene, 2012). However, including interaction terms across levels in hierarchical data presents a problem. When examining hierarchical data in the framework of regression analysis, the data can either be disaggregated or aggregated. Disaggregation assigns the same school characteristics to all students within the same school, or brings the higher-level data down to a lower level of analysis. The obvious problem here is that all students within a particular school have similar characteristics.

When adding interaction terms across levels of analysis, it then becomes difficult to determine the true group effects given that the observations are highly correlated (Kreft, 1996). Aggregation would involve bringing the variables "up" or using school-level variables to comment on average school achievement (Osborne, 2000). Here, the issue becomes a loss of individual variability and either overestimating or underestimating interaction terms (Raudenbush & Bryk, 2002).

In the context of multilevel models, cross-level interactions, or looking at relationships between independent variables at a higher level and the dependent variable is expected. Multilevel modeling allows for true modeling of cross-interaction terms, as this method accounts for the nested nature of the data while estimating equations for each level of analysis (Kreft, 1996; Osborne, 2000; Raudenbush & Bryk, 2002). For these reasons, a comparison of multilevel modeling and regression analysis will be made to not only test model fit for the data but to also help future researchers who struggle with similar questions.

6.5 Methodology

Through the use of educational production functions, I sought to predict a student's financial knowledge as shown by the PISA 2012 Financial Literacy Assessment. When using educational production functions, the output is typically represented as a student's "output" on an assessment (i.e. student performance) and inputs are characteristics of the students, teachers, schools, etc. Educational production functions gained popularity due to Hanushek (1979, 1986) who first determined that higher achievement levels were linked to better teachers and higher quality schools. Over time, many economists conducting educational research were able to successfully use educational production functions with a variety of inputs and outputs (Hanushek, 1997; Hedges, 1994; Krueger, 1999; Rothstein, 2010).

A standard educational production function is estimated using the following form:

$$Y_{isc} = \alpha + \beta_1 G_{isc} + \beta_2 X_{isc} + \beta_3 S_{isc} + \beta_4 C_{isc} + \varepsilon_{isc} \quad (18)$$

where Y_{isc} is the overall achievement in financial literacy for student *i* in school *s* in country *c*.

G_{isc} is a dummy variable taking the value of 1 if the student is female.

X_{isc} is a vector of student characteristics, other than student gender.

S_{isc} is a vector of school characteristics.

C_{isc} is a vector of country-level characteristics.

ε_{isc} is a normally distributed error term.

This production function will provide the basis for both the multilevel analyses and the regression analyses. When estimating models using both multilevel modeling and regression, model estimates are examined to provide a methodological comparison. In addition to model estimates, standard errors, heteroscedasticity, and variance for the two methodological approaches are examined.

6.5.1 Multilevel Modeling

In previous chapters, multilevel models were built to examine student financial knowledge and the gender gap in student financial knowledge on the PISA 2012 Financial Literacy Assessment. More specifically, Chapter 4 examined financial knowledge and the gender gap in financial knowledge by examining parental characteristics with three-level hierarchical models. The models built in Chapter 4 were random-coefficient models. Random-coefficient models combine fixed effects and random effects together in hierarchical models. With these types of models, the level-1 intercept, or the average student performance across schools and countries, is predicted by at least one level-1 variable. Here, the variables used were a series of parental characteristics. For random-coefficient models, a regression line for each school is estimated and averaged across all schools. The same process applies to the sample of countries. Thus, the estimates produced are averages of the fixed effects at the student level as well as the random effects at the school and country levels (Garson, 2013; Raudenbush & Bryk, 2002). The models built in Chapter 4 utilized only the finalized student-level weight to account for differing sample sizes of students within schools and countries.

Chapter 5 examined student financial knowledge across students in a variety of countries in relation to country-level variables using different three-level hierarchical models. The multilevel models estimated in Chapter 5 are classified as slopes-and-intercepts models within a hierarchical linear modeling framework. Slopes-and-intercepts models use both fixed effects and random effects to estimate the variability of both the intercepts and slopes across the higher levels of grouping. For the three-level models estimated here, the country-level variables, or the level-3 variables, are used to estimate the student intercept (average student performance) and whether it randomly varies; additionally, the gender slope as an outcome can be estimated as a random factor by the level-3 country characteristics. The models built in Chapter 5 utilized two different weighting strategies: one set of models estimated used both student- and school-level weights, while another set of models utilized only the student-level weight. For the purpose of comparison in this chapter, only the models using the student-level weight will be examined.

6.6 Parent Results

6.6.1 Descriptive Statistics of Parental Characteristics Analyses

Parent analyses are conducted on a sample of 9,929 students from 3,964 schools in 18 different countries. This subsample was created due to missing data at the student level. A discussion of the missing data can be found in Section 4.3.1. Table 6.1 contains information regarding sample sizes of students and schools within each country represented.

Table 6.1 Sample Sizes for Schools and Students within Countries, Restricted Sample, PISA 2012

Country (N=18)	Number of participating schools	Number of participating students
OECD Member Countries/Economies		
Australia	148	248
Flemish Community (Belgium)	29	53
Czech Republic	282	541
Estonia	204	432
France	229	433
Israel	30	54
Italy	1,061	3,149
New Zealand	148	344
Poland	181	449
Slovak Republic	184	431
Slovenia	256	558
Spain	188	441
United States	151	1,071

Table 6.1 continued

Non-OECD Member Countries/Economies		
Colombia	315	1,902
Croatia	160	1,126
Latvia	190	895
Russian Federation	212	1,138
Shanghai-China	153	1,180
Total	4,927	27,057

Table 6.1 is identical to Table 4.1 from Chapter 4 and Table 5.2 from Chapter 5. A discussion of the findings from this table can be found in Section 4.3.1. Variables used in analyses include parental characteristics reported by students in order to examine the relationships between parents and student financial knowledge. Table 6.2 contains means, standard deviations, sample sizes, and variable explanations for each variable used in subsequent parental characteristic analysis.

Table 6.2 Sample Means, Restricted Sample, Parent Analyses, PISA 2012

Variable	Mean	Explanation
Male	0.50 (0.50)	0 = Female 1 = Male
Mother's Highest Level of Schooling (Mother's Highest Schooling)	4.31 (0.92)	1 = Did not complete ISCED level 1 2 = ISCED, level 1 3 = ISCED, level 2 4 = ISCED, level 3B, 3C 5 = ISCED, level 3A
Mother's Employment Status (Mother Employment)	0.72 (0.45)	0 = not employed 1= employed

Table 6.2 continued

Father's Highest Level of Schooling (Father's Highest Schooling)	4.23 (0.96)	1 = Did not complete ISCED level 1 2 = ISCED, level 1 3 = ISCED, level 2 4 = ISCED, level 3B, 3C 5 = ISCED, level 3A
Father's Employment Status (Father Employment)	0.89 (0.31)	0 = not employed 1= employed
Mother Lives in Student's Household (Mother Lives in Home)	0.96 (0.18)	0 = No 1 = Yes
Father Lives in Student's Household (Father Lives in Home)	0.88 (0.32)	0 = No 1 = Yes
How often Student Talks to Parents or Other Adults about Money Matters (Talk about Money)	2.49 (0.96)	1 = Never or hardly ever 2 = Once or twice a month 3 = Once or twice a week 4 = Almost every day
Learned to manage money in school (Learn about Money in School)	0.36 (0.48)	0 = No 1 = Yes
Student's Socioeconomic Status (ESCS)	-0.003 (16.59)	Index of economic, social, and cultural status

Note: Standard deviations in parentheses.
Note: ISCED stands for International Standard Classification of Education
Note: ISCED, level 3A = Upper secondary with access to level 5A (theoretically-oriented post-secondary); ISCED, level 3B = Upper secondary with access to level 5B (technically-oriented post-secondary); ISCED, level 3C = upper secondary with access to level 4 (post-secondary non-tertiary); ISCED, level 2 = lower secondary; ISCED, level 1 = primary education. For more information, see http://www.oecd.org/education/skills-beyond-school/1962350.pdf

Table 6.2 is identical to Table 4.2 from Chapter 4. A full discussion of this table can be found in Section 4.3.1.

6.6.2 Multilevel Model Estimates – Parental Characteristics

To examine the correlations between parental characteristics and student financial knowledge, as well as the correlations between parental characteristics and the gender gap in financial knowledge, four multilevel models are estimated. The models estimated are identical to those estimated in Chapter 4. Model 1 examines a student's socioeconomic status and whether or not the student learned to manage money in school. Model 2 adds gender in order to examine the gender gap in achievement. Model 3 adds parental characteristics as predictors of a student's financial knowledge, and Model 4 adds interactions between the student's gender and all parental characteristics. Table 6.3 presents model estimates using multilevel modeling analysis of how the student's gender and parental characteristics are related to financial knowledge.

Table 6.3 Multilevel Regression Estimates of Predictors of Financial Knowledge, Fixed Effects, Parent Analyses, PISA 2012

	Model 1	Model 2	Model 3	Model 4
Fixed Effects				
Intercept	505.19**** (7.00)	499.95**** (7.47)	426.43**** (11.08)	427.31**** (12.77)
ESCS	35.25**** (0.94)	34.11**** (0.92)	29.17**** (1.18)	29.01**** (1.18)
Learn about Money in School	3.56* (1.78)	3.73* (1.75)	3.39 (1.75)	3.26 (1.75)
Male		12.10**** (2.24)	12.53**** (2.21)	13.67 (14.06)
Mother's Highest Schooling			3.50*** (1.17)	6.61**** (1.48)
Mother Employment			6.07*** (1.97)	10.37**** (2.61)
Father's Highest Schooling			3.47*** (1.08)	0.87 (1.39)
Father Employment			-7.87** (2.74)	-7.68* (3.56)
Mother Lives in Home			29.61**** (4.89)	29.16**** (7.11)
Father Lives in Home			9.72*** (2.62)	5.77 (3.46)
Talk about Money			3.44**** (0.89)	2.71** (1.19)

Table 6.3 continued

Male*Mother's Highest Schooling				-7.35***
				(2.19)
Male*Mother Employment				-7.88*
				(3.90)
Male*Father's Highest Schooling				6.01**
				(2.05)
Male*Father Employment				-1.20
				(5.53)
Male*Mother Lives in Home				0.003
				(9.81)
Male*Father Lives in Home				9.19
				(5.25)
Male*Talk about Money				1.47
				(1.78)
% of level-1 variance explained	0.10	0.30	0.31	0.31
% of level-2 variance explained	0.23	0.30	0.31	0.31

Note: ****p<0.001; ***p<0.01; **p<0.05; *p<0.10
Note: Standard errors in parentheses

Table 6.3 is identical to Table 4.4. Results from this table are discussed in full in Section 4.3.2. The table is reproduced here in order to later make comparisons to the regression models.

6.6.3 Regression Estimates – Parental Characteristics

To make a methodological comparison, models examining parental characteristics and student financial knowledge are estimated using regression analysis. More specifically, the model estimates are obtained using cluster-robust, weighted linear regression to correct for the heteroscedasticity present in the same subset of data as well as to account for differences in sample sizes across countries. Models 1 – 4 use the same independent variables as with multilevel modeling procedures, though estimates do vary. Table 6.4 presents model estimates for Models 1 – 4 using regression analysis.

Table 6.4 Regression Estimates of Predictors of Financial Knowledge, Parent Analyses, PISA 2012

	Model 1	Model 2	Model 3	Model 4
Fixed Effects				
Intercept	501.20****	496.87****	485.63****	480.02****
	(2.01)	(2.53)	(13.33)	(18.95)
ESCS	36.68****	36.57****	30.81****	30.76****
	(1.99)	(2.00)	(2.66)	(2.64)
Learn about Money in School	0.54	0.65	0.28	0.35
	(3.87)	(3.86)	(3.84)	(3.83)
Male		8.82**	9.55***	-8.58
		(3.53)	(3.52)	(26.10)
Mother's Highest Schooling			-2.21	-4.20
			(2.55)	(3.34)
Mother Employment			-3.77**	-4.95*
			(1.49)	(2.08)
Father's Highest Schooling			-4.64*	-3.18
			(2.36)	(2.97)
Father Employment			-0.80	-0.48
			(2.24)	(2.83)
Mother Lives in Home			22.12*	34.10**
			(11.40)	(16.57)
Father Lives in Home			6.28	2.54
			(6.06)	(8.73)
Talk about Money			1.78	1.73
			(1.86)	(2.63)
Male*Mother's Highest Schooling				4.71
				(4.69)
Male*Mother Employment				2.37
				(2.90)
Male*Father's Highest Schooling				-3.31
				(4.62)
Male*Father Employment				-0.24
				(4.45)
Male*Mother Lives in Home				20.59
				(22.18)
Male*Father Lives in Home				-8.13
				(12.09)
Male*Talk about Money				-0.10
				(3.64)
Adjusted R^2	0.136	0.138	0.146	0.146
F	781.04	530.29	170.35	101.15

Note: ****p<0.001; ***p<0.01; **p<0.05; *p<0.10
Note: All standard errors and p-values reported are for cluster-robust estimators.
Note: Standard errors in parentheses.

Model 1 controls for the student's socioeconomic status (*ESCS*) and the student's opportunity to learn by using the variable *Learn about Money in School.* Model estimates indicate that *ESCS* is positive and significant. If a student has above average socioeconomic status, this is associated with an expected increase in their financial knowledge on the PISA Financial Literacy Assessment by almost 37 points. The opportunity to learn measure was not significant in this model.

To examine the relationship between the student's gender and financial knowledge, *Male* is added in Model 2. The coefficient on *Male* indicates that male students have more expected knowledge than female students. More specifically, male students are expected to outperform female students by almost 9 points. This finding is consistent with previous research, which has indicated a gender gap in the financial knowledge of high school students favoring male students (Becchetti et al., 2013; Lührmann et al., 2012). The student's socioeconomic status remains similar to Model 1, and the student's opportunity to learn is once again not significant.

Model 3 examines parental characteristics in the context of student financial knowledge. Variables included in this model are identical to those from Model 3 in Table 6.3. *ESCS* and *Male* have similar estimated coefficients than in Model 2, whereby students with higher socioeconomic statuses are likely to be more financially knowledgeable, and male students outperform female students by almost 10 points. Model 3 also shows that many parental characteristics are correlated with a child's financial knowledge. For example, the coefficient on *Mother Employment* indicates that having a mother with a job is associated with a decrease in financial knowledge. Also, the more education the student's father has, the less financial knowledge the student is expected to have, as indicated by the negative, significant coefficient on

Father's Highest Schooling. Once again, having a mother live in the same household is associated with an increase in student financial knowledge, though the coefficient is only marginally significant.

In addition to the independent variables included in Model 3, Model 4 adds interaction terms between the student's gender and parental. None of the interaction terms are significant in this model. Also to note is that there is no significant gender gap in this model.

6.6.4 Parental Characteristics – Comparing Multilevel Models and Regression Analyses

To compare methodological approaches, both multilevel models and regression models are estimated in order to assess which methodology is not only most applicable for the research questions asked but also which is more applicable for the dataset used. In order to compare the methodologies, estimates and standard errors are first compared. Model fit and model diagnostics are also compared to assess the methodologies. Evidence from these comparisons help to determine which methodological approach is most applicable to determine the relationship between parental characteristics and the student financial knowledge demonstrated on the PISA 2012 Financial Literacy Assessment.

To compare model estimates and standard errors, Table 6.3 is used for multilevel models, and Table 6.4 is used for regression analysis. It should be noted that the models estimated in Table 6.3 and Table 6.4 use the same sample of students, the same dependent variable, the same independent variables, and the same weighting strategy (student-level weight only). Across the models estimated, the multilevel models estimate a larger coefficient on *Male*, indicating a more pronounced gender gap between male and female students. For example, in Model 2, the coefficient on *Male* from Table 6.3 (the multilevel model) is 12.10, while the coefficient on *Male* from Table 6.4 (the regression analysis) is 8.82. When examining parental characteristics and interactions between parental characteristics and gender, the multilevel models in Table 6.3 report more significant coefficients than in the regression models from Table 6.4. In the multilevel Model 4 from Table 6.3, the coefficients that are statistically significant include *Mother's Highest Schooling, Mother Employment, Father Employment, Mother lives in home,* and *Talk about money,* as well as the interactions *Male*Mother's Highest Schooling, Male*Mother Employment,* and *Male*Father's Highest Schooling*. In the same model (Model 4), regression estimates from Table 6.4 report the only significant coefficients are for *Mother Employment* and *Mother Lives in Home*. Previous research predicts that using regression analysis when multilevel modeling is more appropriate leads to Type I error, or detecting statistical relationships that are not actually present in the data (Huta, 2014; Steenbergen & Jones, 2002). Here, however, it appears that Type II error is present in the regression models, whereby models fail to detect many statistical relationships present in the nested data. However, before concluding that the multilevel models are in fact detecting correct statistical relationships, other attributes need to be examined.

Previous research comparing weighted regression analyses and multilevel models has indicated that standard error estimates in weighted regression models tend to be smaller in nested data (Ammermuller et al., 2005). Results from the models are mixed, as some standard errors are smaller and some are larger. When comparing Model 1, the standard errors in the regression estimates from Table 6.4 are almost always smaller than those in Table 6.3. However, the standard errors are larger in the regression estimates from Model 2. Models 3 and 4 showed mixed results, where some of the standard errors are smaller and some are larger. From these results, it is thus difficult to determine whether or not regression estimates or multilevel model estimates are more appropriate here. It should be noted that the standard errors reported in Table 6.5 are all heteroscedasticity-adjusted standard errors. If this were not the case, standard errors would consistently be smaller than those in the multilevel models. However, this did not occur with the data here.

Nested data will inherently share some variance among observations, as observations are nested within certain common hierarchical structures. In the case of the PISA 2012 data, individual student observations may share variance if they are in the same school and/or the same country. This causes a problem for regression models, as one of the underlying assumptions of regression estimation is that the error terms have equal variance, or that no heteroscedasticity, or unequal variance, is present (Greene. 2012). Before the regression models were run, heteroscedasticity was detected from an examination of the residual plots in each of the models. Thus, White's procedure was used to obtain heteroscedasticity-consistent estimators, or robust standard errors (White, 1980). This process yielded larger standard errors and smaller t-values with no change to the parameters (Schütz, 2009). When examining the models in Table 6.4, it does appear that there is still some heteroscedasticity present in some of the models run. Specifically, when examining the plots of residuals for each observation, the tails of the plots for Models 2-4 appear to deviate from the norm, which indicates the presence of heteroscedasticity (Greene, 2012). Multilevel models can handle heteroscedasticity, as this procedure assumes unequal variances

(Raudenbush & Bryk, 2002). Thus, in terms of accounting for the variance structure of the data, multilevel models appear to be the best fit.

To that end, the multilevel models estimated in Table 6.3 account for more variance explained at the student level than the regression models in Table 6.4. An r-squared value is simply the amount of variance explained by the model (Gujarati & Porter, 2009), and these models explain up to 14% of the variance in student scores. When examining intraclass correlations, or the amount of variance at each level of analysis prior to estimation, a significant amount of variance in knowledge lies at the school level (30%) and the country level (8%) when examining the unconditional model.[13] Also, Table 6.3 indicates that the models estimated can explain up to 31% of the variance in student scores at the student level (level 1) and at the school level (level 2). In light of the variance at each level prior to estimation as well as the percentage of variance explained by each multilevel model, multilevel modeling appears to be more appropriate given the variance structure of the data. In the case of the models estimating student financial knowledge and parental characteristics, it appears as though multilevel models are a better fit for the data.

6.7 Country Results – Unrestricted Sample

6.7.1 Descriptive Statistics of Country-Level Variables – Unrestricted Sample

Analyses of country-level variables are conducted on a sample of 27,057 students from 4,927 schools in 18 countries. The sample was decreased from an

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[13] A full discussion of the unconditional model and intraclass correlation can be found in Chapter 4, Section 4.3.2.

original sample size of 29,041 students due to missing data at the student and country levels. The sample of 27,057 students will henceforth be referred to as the unrestricted sample. Table 6.5 shows sample sizes for schools and students within countries for the unrestricted sample.

Table 6.5 Sample Sizes for Schools and Students within Countries, Unrestricted Sample, PISA 2012

Country (N=18)	Number of participating schools	Number of participating students
OECD Member Countries/Economies		
Australia	745	3,132
Flemish Community (Belgium)	155	1,042
Czech Republic	240	1,007
Estonia	200	1,080
France	199	934
Israel	153	987
Italy	1,061	6,474
New Zealand	156	827
Poland	165	991
Slovak Republic	218	1,018
Slovenia	289	1,237
Spain	165	1,016
United States	151	1,071
Non-OECD Member Countries/Economies		
Colombia	315	1,902
Croatia	160	1,126
Latvia	190	895
Russian Federation	212	1,138
Shanghai-China	153	1,180
Total	4,927	27,057

Table 6.5 is identical to Table 5.1 from Chapter 5. Findings from this table are discussed in full in Section 5.3.

The independent variables in these analyses occur at the student level and the country level. The student-level variables are the student's gender and the student's socioeconomic status. The independent variables at the country level include the real GDP per capita, the labor force participation rate, the labor force participation rate for women, the unemployment rate, and whether or not the country is an OECD member. Table 6.6 displays means, standard deviations, and specific variable explanations for the variables of interest in the country analyses.

Table 6.6 Sample Means, Country Analyses, PISA 2012

Student-Level Variable	Mean (unrestricted) (n=27,057)	Mean (restricted) (n=9,929)	Explanation
Male	0.50 (0.50)	0.50 (0.50)	0 = Female 1 = Male
Student’s Socioeconomic Status (ESCS)	-0.08 (0.96)	0.00 (0.94)	Index of economic, social, and cultural status
Country-Level Variable	**Mean (unrestricted) (n=18)**	**Mean (restricted) (n=18)**	**Explanation**
GDP	$20,437.27 (12,858.23)	$20,437.27 (12,858.23)	GDP Per Capita 2011 (in constant 2005 US$)
LFPR	0.60 (0.06)	0.60 (0.06)	Labor Force Participation Rate (%)
LFPRw	0.53 (0.06)	0.53 (0.06)	Labor Force Participation Rate - Women (%)
Unemployment	0.10 (0.04)	0.10 (0.04)	Unemployment Rate (%)
OECD	0.72 (0.46)	0.72 (0.46)	0 = non-OECD member 1 = OECD member

Note: GDP, LFPR, LFPRw, and Unemployment were obtained via the World Bank at http://data.worldbank.org/
Note: Standard deviation in parentheses.

Table 6.6 is identical to Table 5.3. A full discussion of findings from the table can be found in Section 5.3.

6.7.2 Multilevel Model Estimates – Country-Level Variables – Unrestricted Sample

Three multilevel models examining the relationships between a student's financial knowledge and country-level variables are built. These multilevel models examine not only the relationships between variables but also the amount of variance explained. Table 6.7 presents multilevel modeling estimates for the country models using the unrestricted sample.

Table 6.7 Multilevel Regression Estimates of Predictors of Financial Knowledge, Fixed Effects, Unrestricted Sample, Country Analyses, Student-Level Weight, PISA 2012

	Model 1	Model 2	Model 3
Fixed Effects			
Level 1			
Intercept	495.51***	495.81***	495.76***
	(9.21)	(15.25)	(11.01)
Male	3.58*	3.31*	3.45*
	(1.38)	(1.28)*	(1.23)
ESCS	25.67***	25.57***	25.61***
	(1.89)	(2.73)	(2.18)
Level 3 – Intercept-as-Outcome			
GDP		0.0001	0.00004
		(0.001)	(0.0008)
OECD		23.96	17.91
		(28.55)	(26.32)
LFPRw		387.26	
		(326.20)	
LFPR			260.26
			(213.68)
Unemployment		-97.62	-145.90
		(206.18)	(173.53)

Table 6.7 continued

Level 3 – Gender Slope-as-Outcome			
GDP		-0.00004	-0.00005
		(0.0001)	(0.0001)
OECD		0.50	0.66
		(4.09)	(16.38)
LFPRw		-42.28*	
		(14.29)	
LFPR			-40.46*
			(16.38)
Unemployment		-49.48	-48.88
		(31.01)	(31.94)
% of level-1 variance explained	0.05	0.05	0.05
% of level-2 variance explained	0.26	0.26	0.26
% of level-3 variance explained	0.18	0.27	0.25

Note: ***p<0.001; **p<0.01; *p<0.05
Note: Standard error in parentheses.

Table 6.7 is identical to Table 5.8. A full discussion of findings from the table can be found in Section 5.4.2.

6.7.3 Regression Estimates – Country-Level Variables – Unrestricted Sample

Regression models examining the relationships between a student's financial knowledge and a country's economic condition are built using the unrestricted sample. The model estimates are obtained using cluster-robust, weighted linear regression to correct for heteroscedasticity present in the data as well as to account for differences in sample sizes across countries. Table 6.8 presents regression estimates with country-level variables for the unrestricted sample.

Table 6.8 Regression Estimates of Predictors of Financial Knowledge, Unrestricted Sample, Country Analyses, PISA 2012

	Model 1	Model 2	Model 3
Intercept	497.11****	483.37****	479.03****
	(2.49)	(20.85)	(26.74)
Gender	8.81**	-19.49	-35.42
	(3.53)	(28.77)	(36.87)
ESCS	36.57****	36.64****	36.60****
	(2.00)	(1.98)	(1.98)
GDP		0.00007	0.00008
		(0.00023)	(0.00022)
LFPR			0.58
			(0.39)
LFPRw		0.58*	
		(0.34)	
Unemployment		-1.26***	-1.21***
		(0.45)	(0.46)
Gender*GDP		-0.0002	-0.0001
		(0.0003)	(0.0003)
Gender*OECD		6.10	6.46
		(9.55)	(9.49)
Gender*LFPR			0.61
			(0.54)
Gender*LFPRw		0.42	
		(0.47)	
Gender*Unemployment		0.71	0.79
		(0.30)	(0.68)
Adjusted R^2	0.14	0.14	0.14
F	795.20	169.92	169.50

Note: ****p<0.001; ***p<0.01; **p<0.05; *p<0.10
Note: Standard error in parentheses.

Regression models estimate relationships across the entire sample of students without accounting for the different levels of analysis. In Model 1, the intercept, or average student performance, the student's socioeconomic status *(ESCS),* and the student's gender *(Male)* are significantly correlated with student financial knowledge. With regression analyses, there is a gender gap in financial knowledge between males and females, and students from more advantaged socioeconomic backgrounds are likely to have more financial knowledge. Models 2 and 3 examine the relationships between a student's financial knowledge and many country-level variables. The country-level variables used in these models are identical to those used in Section 6.6.6 for the multilevel models estimated. Models 2 and 3 also make use of interaction terms between the student's gender and the country-level variables. This is done to draw comparisons to the gender slopes-as-outcome findings when using multilevel modeling estimation procedures. In model 2, the intercept and *ESCS* remain significant, but *Male* is no longer significant. In terms of the country-level variables, *LFPRw* and *Unemployment* are significant in Model 2. The coefficient on *LFPRw* indicates that every one percent increase in the labor force participation rate for women is associated with a 0.58 point increase in student financial knowledge. While the magnitude of the coefficient is small, it is still statistically significant. The negative coefficient on *Unemployment* indicates that a decrease in the unemployment rate is associated with an increase in financial knowledge. None of the interaction terms between *Male* and the country-level variables are significant, indicating no correlational relationships between a country's economic landscape and the gender gap in this sample. The results of Model 3 are similar to those of Model 2, except that *LFPR* is not statistically significant. There is once again no gender gap present in this model, *ESCS* remains significantly correlated with financial knowledge, and none of the interactions terms are significant. *Unemployment* remains negative and statistically significant, so that a decrease in the unemployment rate is associated with a significant increase in student knowledge.

6.7.4 Country Characteristics – Comparing Multilevel Models and Regression Analyses using the Unrestricted Sample

A similar methodological comparison of multilevel modeling and regression models of country-level variables is conducted for the unrestricted sample of students. Model estimates and model fit are examined to determine whether multilevel modeling or regression analysis is most appropriate for the data and research questions presented in this discussion. For the purpose of this section, Table 6.7 presents multilevel model estimates and Table 6.8 presents regression estimates of the relationship between student financial knowledge and country characteristics for the unrestricted sample of students.

In terms of model estimates, the methodology does change model estimates. Both the multilevel model estimates and regression model estimates report statistically significant relationships between a student's financial knowledge and a student's socioeconomic status *(ESCS).* Yet, the estimates are higher for the intercept in the multilevel models and lower for *ESCS* in the regression models. As mentioned before for multilevel modeling estimates, the labor force participation rates used are marginally statistically significant in predicting the gender slope. The results suggest that country-level variables are not related to either average student performance or the gender gap. The regression models, however, detect highly statically significant findings. Table 6.8 shows statistically significant relationships between the unemployment rate and a student's financial knowledge. None of the interaction terms between the student's gender and the country-level variables are statistically significant. When nested data is present and regression models are estimated, Type I error occurs (Huta, 2014; Steenbergen & Jones, 2002). When comparing the estimates in Table 6.9 with those from Table 6.10, Type I error is present, therefore indicating that multilevel modeling is more appropriate for the nested nature of the data. To that end, the standard errors for the regression models are almost always lower than those in the multilevel models, which is a consequence of either Type I error or heteroscedasticity (Ammermüller et al., 2005; Greene, 2012; Gujarati & Porter, 2009; Steenbergen & Jones, 2002).

Having individual observations nested within levels, such as in schools and countries, creates an issue, as observations will share variance. This, in turn, will cause unequal variance among observations and thus unequal error terms. An assumption of regression estimation is that all error terms have equal variance, and therefore exhibit no heteroscedasticity (Greene, 2012). In the regression analysis, heteroscedasticity is present both before and after cluster-robust procedures were used. Residual plots of the cluster-robust estimates still show unequal error terms. As previously mentioned, in the presence of heteroscedasticity, multilevel modeling procedures are more applicable, as multilevel model accounts for unequal variance and spreads the variance among the levels of hierarchy (Garson, 2013). Multilevel modeling even allows for multiple error terms, one for each level of analysis (Raudenbush & Bryk, 2002). From a variance perspective, multilevel modeling appears to fit the data best.

6.8 Country Results – Restricted Sample

6.8.1 Descriptive Statistics of Country-Level Variables – Restricted Sample

Country analyses are also conducted on a smaller student sample, the same sample of students used in analyses of parental characteristics. This sample will henceforth be referred to as the restricted sample. The restricted sample contains 9,929 students from 3,964 schools in 18 countries. Table 6.1 shows the sample sizes for schools and students within countries for the restricted sample. Given that Table 6.1 is identical to Table 4.1, a detailed discussion of the sample can be found in Section 4.3.1.

Means, standard deviations, and specific variable explanations of the restricted sample can be found in Table 6.6 in section 6.7.1. Given that Table 6.6 is identical to 5.3, a detailed discussion of the findings in the table can be found in Section 5.3.

6.8.2 Multilevel Model Estimates – Country-Level Variables – Restricted Sample

Three multilevel models examining the relationships between country-level variables, average student performance, and the gender gap are examined. Models 1 – 3 mimic those models built in section 6.7.2 except for the fact that the restricted sample is used. Table 6.9 presents the resulting model estimates.

Table 6.9 Multilevel Regression Estimates of Predictors of Financial Knowledge, Fixed Effects, Restricted Sample, Country Analyses, Student-Level Weight, PISA 2012

	Model 1	Model 2	Model 3
Fixed Effects			
Level 1			
Intercept	502.36***	502.38***	502.42***
	(5.57)	(5.35)	(5.36)
Male	11.41***	11.99***	12.05***
	(2.77)	(2.24)	(2.09)
ESCS	33.41***	33.30***	33.33***
	(2.16)	(2.18)	(2.18)

Table 6.9 continued

Level 3 – Intercept-as-Outcome			
GDP		-0.0002	-0.0002
		(0.0006)	(0.0006)
OECD		-2.00	-0.97
		(10.97)	(11.43)
LFPRw		95.36	
		(83.17)	
LFPR			94.50
			(92.49)
Unemployment		-47.33	-41.67
		(74.12)	(72.72)
Level 3 – Gender Slope-as-Outcome			
GDP		0.0005	0.0001
		(0.0002)	(0.0002)
OECD		-0.97	-0.50
		(8.13)	(7.51)
LFPRw		64.84	
		(31.40)	
LFPR			88.05*
			(34.79)
Unemployment		66.82	77.38
		(51.86)	(53.61)
% of level-1 variance explained	0.29	0.29	0.29
% of level-2 variance explained	0.44	0.44	0.43

Note: ***p<0.001; **p<0.01; *p<0.05
Note: Standard error in parentheses.

Table 6.9 is the same as Table 5.12. Results of this table were previously discussed in Section 5.4.5.

6.8.3 Regression Estimates – Country-Level Variables – Restricted Sample

For a methodological comparison, regression models examining the relationships between a student's financial knowledge and a country's economic conditions are built. The model estimates are obtained using cluster-robust, weighted linear regression to correct for the heteroscedasticity present in the data as well as to account for differences in sample sizes across countries. Models 1 – 3 are identical to those in Section 6.7.3 except for the sample used. All regression models are estimated using SAS® 9.2 software. Table 6.10 presents regression estimates with country-level variables for the restricted sample.

Table 6.10 Regression Estimates of Predictors of Financial Knowledge, Restricted Sample, Country Analyses, PISA 2012

	Model 1	Model 2	Model 3
Intercept	494.69****	396.80****	393.68****
	(0.93)	(7.53)	(9.52)
Gender	0.92	15.51	16.83
	(1.40)	(11.29)	(14.31)
ESCS	39.93****	38.82****	39.69****
	(0.78)	(0.77)	(0.77)
GDP		-0.0004****	-0.0004****
		(0.0001)	(0.0001)
OECD		14.41****	13.75****
		(3.08)	(3.07)
LFPR			210.48****
			(13.81)
LFPRw		232.75****	
		(11.58)	
Unemployment		-228.88****	-241.57****
		(22.36)	(22.99)
Gender*GDP		0.00006	0.00006
		(0.00015)	(0.00015)
Gender*OECD		0.37	0.53
		(4.59)	(4.57)
Gender*LFPR			-28.97
			(20.91)
Gender*LFPRw		-30.31	
		(17.55)	
Gender*Unemployment		-7.48	-4.84
		(32.74)	(33.57)
Adjusted R^2	0.14	0.18	0.17
F	795.20	612.88	573.93

Note: ****p<0.001; ***p<0.01; **p<0.05; *p<0.10
Note: Standard error in parentheses.

In Model 1, the intercept and the student's socioeconomic status *(ESCS)* are significant predictors of a student's financial knowledge. There is no gender gap present in Model 1, as the coefficient on *Male* is not significant. Therefore, there is no significant difference present in the financial knowledge of male and female students. In Model 2, when adding country-level variables, many relationships appear. *GDP* is negative and significant, indicating that a decrease in the real GDP per capita of a country is associated with a decrease in financial knowledge. The coefficient on *GDP* is very small, however. If a student comes from an *OECD* member country, as most in the sample of students do, their financial knowledge score on the assessment is expected to increase by 14.41 points. *LFPRw* is positively correlated with student financial knowledge. The coefficient of 232.75 indicates that each one percent increase in the female labor force participation rate is associated with an increase in expected student financial knowledge will increase by over 232 points. Finally, each one percent decrease in the unemployment is associated with an increase in expected student financial knowledge by 228.88 points. None of the interaction terms between a student's gender and country-level variables are significant, however. Model 3 shows similar results to those found in Model 2. At the student level, the intercept and *ESCS* are once again significant predictors, while there is still no gender gap in achievement, as evidenced by the *Male* coefficient being statistically insignificant. *GDP* and *OECD* are statistically significant, and the coefficients are very similar to those in Model 2. The coefficient on *LFPR* indicates that for a one percent increase in the labor force participation rate is associated with an increase in student knowledge of approximately 210 points. On the other hand, a decrease in the unemployment rate by one percent is associated with an increase in student knowledge of approximately 242 points. Again, none of the interaction terms between the student's gender and the country characteristics are significant in Model 3.

6.8.4 Country Characteristics – Comparing Multilevel Models and Regression Analyses using the Restricted Sample

To best assess which methodology is most appropriate for the data and the research questions, both multilevel models and regression models are estimated. Results from these models can be seen in earlier sections, specifically in Section 6.8.2 for the multilevel models and Section 6.8.3 for the regression analysis. Methodologies are compared on the basis of model estimates including standard errors, model fit, and model diagnostics. It should be noted that both modeling procedures used only the student-level weight.

A comparison of model estimates and standard errors will be conducted using the previously reported Table 6.9 for multilevel models and Table 6.10 for regression models. Estimates in Table 6.9 and Table 6.10 were found using the same sample of students in schools and countries as well as the same dependent and independent variables. The only difference between the estimates is the method of estimation. In terms of model estimates, the two methodologies differ in their findings. Across the two methodologies, the intercept and the student's socioeconomic status *(ESCS)* are both significant, though the estimates are larger with multilevel modeling. One difference between the modeling procedures is whether or not a gender gap is present. The multilevel modeling estimates find a gender gap favoring male students, while the regression estimates find no statistically significant differences between the performance of male and female students. This is again an example of Type I error in the regression models (Steenbergen & Jones, 2002). The most striking difference in the model estimates can be seen in the examination of the country-level independent variables. With multilevel modeling, none of the country-level variables used have any statistical relationship with either a student's average financial knowledge, and only one variable in one model is marginally significant in predicating the gender gap. In the regression models, however, variables such as GDP per capita, whether or not the country is an OECD member, the labor force participation rate, and the unemployment rate are highly correlated with a student's financial knowledge across the restricted sample of students. Yet, none of the country-level variables exhibit any statistical relationship with the student's gender. The many more relationships present in the regression models as opposed to the multilevel models can be attributed to Type I error. Steenbergen and Jones (2002) previously reported that not using multilevel modeling with a nested dataset will always lead to Type I error, or detecting statistical relationships that are not actually present. The regression estimates using the nested PISA 2012 data appear to display Type 1 error, and therefore the regression estimates seem to be not as well suited for the data.

In past research, many authors have posited that for nested data analysis, standard errors will be smaller with regression estimates than with multilevel model estimates, due in part to the presence of Type I error (Ammermüller et al., 2005; Steenbergen & Jones, 2002). When comparing results from the PISA 2012 dataset, the standard errors in the fixed estimates appear to almost always be smaller than those in the multilevel modeling estimates, with a few exceptions. The standard errors for the regression estimates in Table 6.10 are cluster-robust standard errors that have been corrected for the presence of heteroscedasticity. Despite the heteroscedasticity correction, the standard errors remain smaller in regression estimates than in the multilevel models. This will, in turn, impact the validity of the models.

It is difficult to make direct comparisons when examining the amount of variance explained by each model. In multilevel models, the amount of variance explained by each model can be determined at each level of analysis. With regression models, however, only one value of variance explained is presented, the r-squared value. An r-squared value is analogous to the amount of student-level variance explained (Gujarati & Porter, 2009; Raudenbush & Bryk, 2002). The multilevel models in Table 6.9 appear to explain more of the variance in student financial knowledge than the regression models in Table 8. The highest r-squared value in Table 6.10 is 0.18, indicating that Model 2 explains 18% of the variance in scores. Yet, all three models in Table 6.9 explain 29% of the variance at the student level and either 43% or 44% of the variance at the school level. It can be argued that the multilevel models are therefore better suited for explaining the variance in the PISA 2012 data. For the models examining relationships between student financial knowledge and country characteristics, multilevel models are the superior methodological approach, as they fit the nested nature of the data and correctly account for the heteroscedasticity that arises.

6.9 Discussion

For the purpose of this chapter, the discussion section will be limited to findings comparing multilevel modeling and regression analysis. An extensive discussion of findings regarding parental characteristics and country-level variables in the context of financial knowledge can be found in Chapter 4 and Chapter 5, respectively. A methodological comparison of multilevel modeling and regression analysis is undertaken in order to identify which methodology is most applicable for the PISA 2012 Financial Literacy Data. Previous chapters examined relationships between parental characteristics and student financial knowledge using multilevel modeling (Chapter 4) and relationships between country-level variables and student financial knowledge using multilevel modeling (Chapter 5). Results from Chapters 4 and 5 are repeated above in this chapter. In addition to the multilevel modeling results, regression models are built with the same data, variables, and weight used in the analyses in Chapter 4 and Chapter 5. When comparing the multilevel modeling results to the regression analysis results, it appears that regression analysis falls short for a number of reasons. In the context of the PISA 2012 dataset, multilevel modeling is the most appropriate methodology approach to answer the research questions asked in Chapters 4 and 5.

6.9.1 Discussion of Parental Characteristics Analyses

In the statistical models examining the role of parental characteristics, both multilevel modeling and regression analysis were used in order to determine which methodology was most appropriate. After comparing model estimates, regression estimates detect many more statistical relationships than multilevel models did. Based on previous research, this should not have been the case. With nested data and regression analysis, Type I error is expected to occur, whereby regression models fail to detect statistical relationships in the data (Huta, 2014; Steenbergen & Jones, 2002). Instead, Type II error is present here, as the regression models showed more statistically significant coefficients on parental characteristics. Type II error is unexpected in this context, and therefore conclusions on the methodological approach could not be determined from looking at the estimates only. Standard errors of the estimates were also examined. With regression analysis and nested data, the standard errors of the regression estimates should be smaller than for the multilevel estimates (Ammermüller et al., 2005). However, this was not always the case. Examining only model estimates did not provide conclusive findings as to which methodology was most appropriate in determining a statistical relationship between parental characteristics and student financial knowledge.

The type of multilevel models estimated to examine parental characteristics are known as random-coefficient models, where both fixed effects and random effects are used to examine how the average performance (the intercept) and the gender slope vary across countries. For an accurate comparison, however, only the fixed effects of the multilevel models are examined and compared to the regression estimates. In the context of the cross-sectional PISA 2012 data, random effects could not be effectively added into models. Regression analysis allows for random effects to be modeled if panel data is present (Greene, 2012). The PISA 2012 data, however, is not an example of panel data. It is difficult to say whether or not comparing regression estimates to the fixed effects in multilevel modeling is the most appropriate comparison that can be made, but it makes the most sense in the context of the models built and the research questions answered. Still, these comparisons alone provide no concrete solution to exactly which methodology should be used to examine the data.

The most compelling examination comes when looking at the heteroscedasticity present in the model. Before final regression models were estimated, regression models not using White's procedure were run to determine whether or not heteroscedasticity was present. Residual plots indicated the presence of unequal variance, so White's procedure was used to correct for heteroscedasticity

(White, 1980). Using this process, standard errors were higher but the parameter estimates remained the same (Schütz, 2009). However, when again examining residual plots for the cluster-robust estimators in the regression models, heteroscedasticity was still present. The presence of heteroscedasticity can influence the outcome of the model, and therefore the regression results should be interpreted carefully. Given the presence of heteroscedasticity and the fact that students are nested within both schools and countries, multilevel modeling seems to be more appropriate. Multilevel modeling allows for multiple error terms, therefore eliminating the issue of unequal variance. Also, instead of minimizing the error of each observation, multilevel modeling uses information from all data points to estimate parameters. Moreover, when examining the variance at each level of hierarchy, it was clear that a good deal of variance lay beyond the student level. Regression analysis cannot easily account for higher-level variance, thus affecting the validity of the model. In light of this information, for parental characteristics analyses, multilevel modeling is the most appropriate methodological approach.

6.9.2 Discussion of Country-Level Variables Analyses

Multilevel models and regression models are estimated in this chapter to examine the role of a variety of country-level variables on student financial knowledge and the gender gap in financial knowledge. Both estimation procedures are used in order to compare the methodologies. In addition to the two methodologies, models are estimated for both an unrestricted sample of students and a restricted sample of students.

In terms of the model estimates, in both the unrestricted and restricted samples, regression models generate Type I error. Previous literature indicated that when comparing regression models to multilevel models, Type I error would occur if the data were hierarchical (Huta, 2014; Steenbergen & Jones, 2002). A regression model exhibiting Type I error indicates possible model misspecification. Multilevel modeling is thus more appropriate when considering the model estimates. In addition to Type I error, previous studies have also indicated that regression models for nested data will have smaller standard errors than those in the multilevel models (Ammermüller et al., 2005). Again in both the unrestricted and the restricted samples, standard errors were smaller in the regression models than in the multilevel models. Schütz (2009) stated that in the case of estimating linear models with hierarchical data, standard errors would be smaller than in hierarchical models, in part due to unequal variance in the data. The regression estimates for both the unrestricted and restricted samples have smaller standard errors, even after using cluster-robust estimators to correct for unequal variance. It is clear that due to Type I error and the smaller standard errors, multilevel modeling is the appropriate methodology.

When examining country-level variables, financial knowledge, and gender, the concern was the fact that cross-level interactions had to be examined (i.e. interactions between student-level variables and country-level variables). To examine cross-level interactions in a regression framework, the data has to be either aggregated or disaggregated. The decision was made to disaggregate the data, so that students from the same country had the same country-level variables. Aggregation of the data was not possible due to the research questions being asked. The disaggregation caused a great deal of dependence in the data, as students from the same country were very similar to one another and not independent. Attempts to correct for this were made, but regression analyses could not correct for the dependence of the data. It could be the case that disaggregation caused Type I error because of the dependence in the data, but it is unclear whether disaggregation or the hierarchical nature of the data caused this issue. Yet, because cross-level interactions needed to be examined, multilevel modeling is more appropriate to do so with the PISA 2012 data.

Heteroscedasticity is once again examined in regression models, and is found even after using White cluster-robust estimators and standard errors. Multilevel modeling accounts for the nested nature of the data and the accompanying heteroscedasticity by spreading the variance among the different levels of analysis and thus different error terms. Similarly to the comparisons of multilevel modeling and regression analyses for the unrestricted sample, multilevel modeling appears to be the most appropriate methodological approach for examining country characteristics in the context of student financial knowledge. In light of the model comparisons, the standard errors, the disaggregation of the data, the cross-level interactions, and the heteroscedasticity present, multilevel modeling was the most appropriate methodical approach in examining country-level variables and financial knowledge.

6.9.3 Limitations

In addition to the limitations mentioned in previous chapters regarding the data itself, one new limitation can be noted in this chapter. The limitation here is the fact that a methodological comparison of the nature presented in this chapter has rarely if ever been undertaken. In fact, no source to date is able to provide concrete reasons for selecting hierarchical linear modeling or regression analysis. No true statistical test exists for cross-sectional data to determine whether or not multilevel models or regression models are more appropriate. However, the analyses in this chapter provide a way for future researchers to examine not only the PISA 2012 data but also any educational data. The analyses in this chapter do not necessarily provide concrete answers for all future questions and datasets, but the compelling results supporting multilevel modeling should show the effectiveness of this methodology. In addition, multilevel modeling is still a developing methodology that is ripe for further analysis. By providing a comparison of multilevel modeling and regression analysis, the hope is to provide guidance for future researchers as well as to provide compelling reasons to use multilevel modeling with hierarchical data.

Chapter 7

DISCUSSION

7.1 Introduction

A renewed emphasis has been placed on increasing the financial knowledge of individuals in light of the global financial crisis of 2009 (OECD, 2014a). Yet, it is not enough to simply say that citizens need to be financially knowledgeable or financially literate. Steps first need to be taken to understand the current state of financial knowledge in order to discuss how it can be improved. Using the PISA 2012 Financial Literacy Assessment, this study examines the financial knowledge of high school-aged students to better assess what teenagers around the world know about financial matters. Additionally, to further understand the financial knowledge of high school-aged students around the world, both parental characteristics and country-level variables are explored to determine if these variables are associated with the financial knowledge of students. The gender gap in financial knowledge is also examined to explain why previous research indicates that males tend to have more financial knowledge than females (Becchetti et al., 2013; Butters et al., 2012; Lührmann et al., 2012; Lusardi et al., 2010; Varcoe et al., 2005). A methodological comparison of multilevel modeling and linear regression is also undertaken through a comparison of results using both types of models.

Results from this study show that parental characteristics are associated with high school-aged students' financial knowledge. In light of these results, financial education programs that promote parental involvement should be encouraged at both the school and country levels. Given that the PISA 2012 dataset represents an international sample of students, country variables such as GDP per capita, labor force participation rates, and unemployment rate are examined to determine whether or not the economic landscape of the students' home country is associated with a student's financial knowledge. In the context of the type of multilevel modeling used, no country-level variables are found to have a significant correlation with a student's financial knowledge on the PISA 2012 Financial Literacy Assessment. This result, however, does not imply that financial knowledge is not influenced by a student's home country. More work should be done on a country-by-country basis to determine appropriate policies to increase the financial knowledge of their citizens and to determine if the cultural and economic differences among a sample of countries influence how much a student knows about financial matters.

Whether or not a gender gap in financial knowledge is present depends on the sample used as well as the weighting strategy used to account for different sample sizes. There is a prominent gender gap in financial knowledge, as indicated in the multilevel models found for the restricted sample in both Chapters 4 and 5 when using only the student-level weight. Here, male students do exhibit more financial knowledge than female students. Yet, no gender gap in financial knowledge is found in multilevel models for both the restricted and unrestricted sample found in Chapter 5 when using both the student- and school-level weights. Therefore, it is unclear as to whether or not a gender gap in financial knowledge exists across the sample of students.

A methodological comparison of multilevel modeling and linear regression is also undertaken to examine the best methodology for analyzing the PISA 2012

Financial Literacy Assessment dataset. Results indicate that multilevel modeling is more appropriate for the research questions being asked. However, there is no statistical test to determine whether or not to use multilevel modeling. Building upon a series of past studies, this dissertation makes the case that multilevel modeling is effective in analyzing the financial knowledge of high school students, despite the fact that both the dataset and the methodological approach are relatively new to financial literacy research.

7.2 Parental Characteristics and Financial Knoweldge

7.2.1 Parental Characteristics Results

When examining the restricted sample of 9,929 students from 3,964 schools in 18 countries, many parental characteristics are associated with student financial knowledge. Multilevel modeling results indicate that both the mother's and father's highest levels of education are positively associated with their child's financial knowledge. Coefficients on the fixed effects indicate that for each change in educational attainment, financial knowledge scores on the assessment are expected to increase by around 3.50 points for both mother's educational levels and father's educational levels. While the coefficient is small, the results seem to suggest that the more education a parent has, the higher the student's expected financial knowledge could be. In the context of financial knowledge, it appears as though having more highly educated adults are associated with more financially knowledgeable teenagers. The employment statuses of both parents are also associated with the amount of financial knowledge a student possesses. If a student's mother works, the student tends to have more financial knowledge; if a student's father works, however, the student tends to have less financial knowledge. It is difficult to pinpoint exactly why this is the case. The negative relationship between fathers who are employed and student financial knowledge is somewhat puzzling. One potential reason for this finding is that working fathers often trade work for spending time with their children, but it is unclear from this analysis alone. In terms of the mother's influence, it could be that children see women moving from the traditional gender role of raising children to working outside the home and are more deeply influenced by this situation.

To that end, the most compelling statistical correlation is seen in whether or not the student's mother lives in the student's household. Having a mother live in the same household as her son or daughter is associated with a significant and large increase in the student's expected financial knowledge; the same cannot be said for a student who has a father live in the household. It is unclear exactly why this correlation is so large, but a few reasons could help to explain the role of mothers on financial knowledge. First, it could be the case that mothers influence overall knowledge by being around their children, thus also influencing financial knowledge. Secondly, it could be that more mothers in the sample have the traditional gender role of raising children and thus children learn more from spending more time with their mothers than with their fathers. While it is not certain why or how having a mother at home influences financial knowledge, the large fixed effect is compelling. Future policies and programs could and should target parental influence in order to increase the financial knowledge of students of all ages.

7.2.2 Parental Characteristics Policy Implications

Past studies have indicated the influence that parents can have on their children's understanding of financial concepts and subsequent financial literacy

(Denhardt & Jeffress, 1971; Mandell & Klein, 2007; Moschis, 1985; Tennyson & Nguyen, 2001; Ward, 1975). In learning more about the financial knowledge of the students in the restricted sample, some policy implications can be suggested to increase the financial knowledge of future students via parental influence. While the influence parents can have on their children's financial knowledge has been well documented, few programs or policies have been put into place to influence the impact that parents can have on their childrens's financial knowledge. Most of the policies suggested will be very general in nature, as it is difficult to select policies and programs that would be applicable for the entire, international sample. Each country has different economic and cultural influences, and thus blanket polices across the sample would not be effective for specific populations of students. Individual countries should examine the financial knowledge of student in their own countries separately and design country- or school-specific policies to address the needs of their students and citizens.

One area that is ripe for the implementation of policies and programs involves college-aged students. Past research examining the role of parental characteristics on the financial knowledge of college-aged students has indicated that parents can have an overall positive influences on the financial knowledge of college students (Chen & Volpe, 1998; Hancock et al., 2012; Jorgensen & Savla, 2010; Lawrence, Cude, Lyons, & Marks, 2006; Norvilitis & MacLean, 2010). In the case of the United States, college is a time when most young adults are first faced with making their own financial decisions, and financial knowledge becomes increasingly important. A possible policy option to influence students via their parents might be to require a brief financial education course for students and parents before students are allowed to take out any student education loans. This policy would only apply to countries where students and/or parents are responsible for the majority of the cost of higher education. A series of websites and tools are available for parents to help them discuss financial matters with their children. Information about these sources can be found in Appendix D. Yet, the burden falls on individual parents as to whether or not they seek out this information and discuss these matters with their children. Considering that many college students are independent or semi-independent, parental influence on money matters needs to happen earlier, especially before students begin making financial decisions that will likely last long into their own adulthoods.

Parents could and should discuss money matters with their children from a young age. The process of consumer socialization indicates that parents are a large aspect of how their children acquire the skills and knowledge to become successful consumers (Dotson & Hyatt, 2005; Jorgensen & Savla, 2010; Moschis, 1985; Ward, 1974). Not much can be done about what students implicitly learn from their parents, but involving parents in the process of teaching their children about financial matters can target explicit learning. Van Campenhout (2015) has suggested a number of options that can be utilized to increase the amount of parental involvement in their children's financial socialization process. The first suggestion is to begin financial education early at home as well as in schools. The idea behind starting early financial education is to teach students before they are faced with financial decision. Also, at a young age, students may be more willing to discuss money matters with their parents and/or they may need their parent's assistance. Currently, very few programs focus on targeting both children and parents. Huang et al. (2013) examined a program where mothers in Oklahoma were encouraged to open college savings accounts for their children. While the authors did not examine the financial knowledge of children, this study provides an example of targeting parental involvement in their children's financial socialization process. Through a series of randomized experiments in Brazil, Bruhn, Leão, Legovini, Marchetti, and Zia (2013) found that involving parents in personal finance workshops and take-home activities led to increased discussions between parents and children about money. Other programs seek to increase parental involvement through the inclusion of homework or other at-home activities with parents, by increasing financial communication in the home, and by increasing school banking programs (Grinstein-Weiss et al., 2011; Johnson & Sherraden, 2007; Van Campenhout, 2015). Overall, however, there is a need for individual countries and schools to reevaluate financial education programs to include more parental involvement (Van Campenhout, 2015). Results from the PISA 2012 Financial Literacy Assessment suggest that parents could influence their children's financial knowledge, and therefore parents should be encouraged to become more involved in financial education initiatives targeted at increasing the financial knowledge of future generations of students and citizens.

7.3 Country-Level Variables and Financial Knowledge

Increased financial knowledge has been associated with better outcomes in individuals, such as increased savings rates and increased investments (Atkinson & Messy, 2012; Atkinson et al., 2007; Hastings et al., 2013; Nicolini et al., 2013). Many societies strive to have financially literate citizens, as increased financial knowledge can cause better societal outcomes (Atkinson & Messy, 2012; OECD, 2014a). Yet, it is unclear exactly why one country or economy may have more financially literate citizens than another country. In the context of the PISA 2012 Financial Literacy

Assessment, country-level variables are examined to determine if a country's economic landscape is associated with the financial knowledge of its high school-aged students.

7.3.1 Country-Level Variables Results

Chapter 5 examines statistical relationships between country-level variables and student financial knowledge as demonstrated on the PISA 2012 Financial Literacy Assessment. Multilevel models are estimated for both a restricted sample of students and an unrestricted sample of students, as well as two different weighting schemes. The restricted sample of students is used in order to make comparisons to the analyses conducted with parental characteristics. Also, analyses using only the student-level weight rather than the student- and the school-level weights are done to also make comparisons to analyses with parental characteristics. The following 2011 country-level variables are included in statistical analyses: GDP per capita; the labor force participation rate; the labor force participation rate for women; the unemployment rate; and whether or not the country was a member of the OECD. In analyses for both the unrestricted and restricted samples of students, none of the country-level variables were significantly correlated with the students' financial knowledge. Previous research had also shown no correlation between variables such as GDP growth and financial knowledge (Jappelli & Padula, 2013; Lo Prete, 2013).[14] The sample of countries used is rather homogenous, in that the countries included have mostly developed, market-based economies with relatively high standards of living. Given a different sample of countries, the country-level variables may have been statistically significant. It is very

[14] For more about the countries included in the dataset, please see Chapter 3.

difficult to model a country's economic and societal landscape with the inclusion of a few variables, and it could be the case that incorrect variables were included to measure the underlying conditions in a country. It is also challenging to determine if societal characteristics are associated with financial knowledge, as variables capturing societal characteristics are difficult to find.

7.3.2 Country-Level Variables Policy Implications

In the sample of 18 countries whose students participated in the PISA 2012 Financial Literacy Assessment, none of the country-level variables included in statistical analyses are statistically correlated with financial knowledge. It is easy to dismiss these results as having no larger implications. However, just because no correlations are found between the country-level variables used and financial knowledge on the PISA 2012 Financial Literacy Assessment does not mean that the country's economic and social landscapes do not matter. Even though country-level variables are not associated with financial knowledge across the sample of students, it should be up to individual countries to determine what policies and programs should be implemented to increase financial knowledge. Many countries have sought to measure the financial knowledge of its citizens and have found that they lack a basic understanding of financial matters (Atkinson & Messy, 2012; Lusardi & Mitchell, 2011; Orton, 2000; Widdowson & Hailwood, 2007). Many of the efforts to measure financial knowledge were made in order to increase financial knowledge within a certain country and were used to justify increased financial education efforts (Becchetti et al., 2013; Lührmann, et al., 2012; Orton, 2000). The United States has also increased its efforts to offer more financial education for high-school aged students (Asarta et al., 2014; Boyce & Danes, 1998; Danes, 2004; Harter & Harter, 2009; Walstad et al., 2010). Policymakers within individual countries should analyze the data separately in order to determine the most appropriate financial education policies and programs.

The OECD (2014a) stated that one of the objectives for administering the financial literacy assessment was for policy makers to have access to data that will inform policy and programmatic decisions. Furthermore, the comparative nature of the dataset ensures that policymakers can compare their schools or countries to others in the sample (OECD, 2014a). The analyses conducted in Chapter 5 were done for the entire sample of students and countries and were therefore not country-specific results. The type of multilevel model used is an intercepts-and-slope-as-outcomes model, which predicts both average student performance across the sample of students and examines the gender gap in achievement (Garson, 2013). These types of models are used in order to more easily compare those results to the linear regression results presented in Chapter 6. Different types of multilevel models could be estimated where each country has its own intercept and slope term, or a linear regression of sorts is fit for each country across the sample (Garson, 2013; Raudenbush & Bryk, 2002). Alternately, if policymakers are interested in learning what their students are capable of accomplishing, they could estimate statistical models restricted to their sample of students. The statistical analysis would depend on the question asked of the dataset. Analyses in this study do not seek to make policy suggestions on a country-by-country basis. Instead, the statistical analyses conducted in this dissertation seek to determine whether or not country-level variables, or the student's country, influence the student's demonstrated financial knowledge.

7.4 Gender Gap Results

One goal in examining the PISA 2012 Financial Literacy Assessment is to determine whether or not there is a difference between the financial knowledge of male and female students. A great deal of previous research found a traditional gender gap in the financial knowledge of high school students, whereby male students had more demonstrated financial knowledge than female students (Becchetti et al., 2013; Butters et al., 2012; Lührmann, et al., 2012; Lusardi et al., 2010; Varcoe et al., 2005). However, many studies also found no statistical differences between male and female high school students (Cameron et al., 2014; Mandell & Klein, 2007; Sohn et al., 2012; Tennyson & Nguyen, 2001; Walstad et al., 2010). Some studies even found that female students had more demonstrated financial knowledge than their male counterparts (Hill & Asarta, 2016; Jang et al., 2014). The gender gap in financial knowledge is examined in both Chapter 4 and Chapter 5. Findings across the chapters are mixed, and depend upon the sample and weighting strategy used. Chapter 4 finds a traditional gender gap in financial knowledge when using the restricted sample and student-level weight. A gender gap favoring males is only present in Chapter 5 when examining the restricted sample and using only the student-level weight. Estimates for the unrestricted sample using both weighting strategies[15] as well as estimates for the restricted sample using both student- and school-level weights find no statistically significant differences between the financial knowledge of male and female students. Additional work aimed at determining whether a gender gap exists within the whole

[15] The two weighting strategies are as follows: the first strategy uses both the student- and school-level weights, while the second strategy uses only the student-level weight.

sample as well as within different countries should be undertaken in order to make policy suggestions.[16]

7.4.1 Gender Gap Results – Parent Models

In the multilevel models examining the relationships between parental characteristics and financial knowledge from Chapter 4, a prominent gender gap in financial knowledge is found, where male students exhibit more financial knowledge than female students. A prominent gender gap is also found using the restricted sample and student-level weight in Chapter 5. Depending on the model specification, the difference between male and female students' scores is around the 12 point range. The gender gap reported is for the restricted sample of 9,929 students and when using the student-level weight only. The models estimated do not account for whether or not a gender gap in financial knowledge exists within a certain school or country. The difference in demonstrated financial knowledge between male and female students is consistent with the findings of previous research examining the gender gap in the financial knowledge of high school-aged students (Becchetti et al., 2013; Butters et al., 2012; Lührmann et al., 2012; Lusardi, et al., 2010; Varcoe et al., 2005).

The gender gap in financial knowledge is somewhat influenced by parental characteristics. Multilevel models from Chapter 4 indicate significant interactions between the student's gender and the mother's highest level of schooling, the student's gender and the mother's employment status, and the student's gender and the father's

[16] Without knowing gender differences or policies in individual countries, it is difficult to comment upon what policies should be implemented. Hung et al. (2012) and OECD (2013b) suggest some country-specific policy considerations and polices.

highest level of schooling.[17] Results suggest that the characteristics of parents can influence their child's understanding of money matters. From a young age, children learn both implicitly and explicit about finances from their parents, and there are often gender differences in the learning process (Dotson & Hyatt, 2005; Edwards et al., 2007; Jorgensen & Savla, 2010; Newcomb & Rabow, 1999). By including parental characteristics in analyses, Chapter 4 sought to examine whether or not parental characteristics influenced the gender gap in knowledge, and some did. Before policy implications are made, however, results from Chapter 5 are examined to see if there is truly a gender gap present in the PISA 2012 Financial Literacy Assessment data.

7.4.2 Gender Gap Results – Country Models

Chapter 5 examined whether or not a gender gap in financial knowledge existed and whether country-level variables were associated with the gender gap in financial knowledge. Two different samples of students are used, the restricted sample of students that was used in Chapter 4, and the larger, unrestricted sample of students.[18]Two different weighting strategies are also used in these analyses. Using intercepts-and-slopes-as-outcomes models, no statistically significant differences in knowledge between male and female students are found in either the unrestricted or restricted samples when using both student- and school-level weights. The finding from the unrestricted dataset using both weights is similar to that of OECD (2014a) for the entire sample of students. Intercepts-as-outcomes models from Chapter 4 using the

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[17] Results are discussed in detail in Chapter 4.

[18] Table 4.1 contains details about the restricted sample, while Table 5.1 contains details about the unrestricted sample.

restricted sample did find statistically significant differences between the financial knowledge of male and female students.

Whether or not a gender gap in financial knowledge actually exists in the PISA 2012 dataset is questionable. It appears as though the weighting strategy and the estimation procedure within the statistical software package used could influence the presence of a gender gap. When using both student- and school-level weights for both the restricted and unrestricted samples, no gender gap is present. However, when using only the student-level weight, a gender gap is present. It can therefore be concluded that the weighting strategy used influences whether or not a gender gap is present. Additionally, two different statistical software packages were used to analyze the data, which could influence the estimates of the gender gap. Chapter 4 utilized the SAS® 9.2 software and Chapter 5 utilized the HLM 7 software. A more detailed discussion of the different types of models and estimation procedures will be discussed later.

7.4.3 Gender Gap Policy Implications

Given that it is difficult to determine with certainty that there are gender differences in the financial knowledge of the male and female students included in the PISA 2012 dataset, it is also difficult to suggest policies that may deal with a gender gap in achievement. The results presented in Chapter 4 identify a gender gap, where male students exhibit more financial knowledge than female students, while the results in Chapter 5 show no significant difference between the financial knowledge of male and female students. These findings are for the entire sample of students and not specific to any one country or school. Before a specific country or school adopts financial education policies, the examination of potential gender differentials in financial knowledge should be undertaken within that specific country or school. As previously mentioned with the overall financial knowledge results, blanket policies for all students in the international sample are not recommended, as they do not account for the many differences between countries and even schools. Hathaway and Khatiwada (2008) have suggested that policies targeting increased financial knowledge should be country specific and should target specific groups of individuals.

Though there is not a clear gender gap present in the PISA 2012 Financial Literacy Assessment data, there could be a traditional gender gap present within an individual country or within an individual school. If this is the case, financial education programs specifically targeting female students should be designed and implemented. At the international level, Hung et al. (2012) examined programs that were specifically targeted to teaching women financial knowledge. Countries such as the United States, Germany, and the United Kingdom have successfully implemented financial education programs for certain subsets of women in order to close the financial education gap between male and female students. Those programs, however, were for adult populations and not for teenagers. To target high school-aged female students, countries and schools should aim to create programs specifically designed for female high school students. The OECD (2013b) has compiled a list of considerations when designing and implementing such programs for girls, such as taking into account the barriers to learning and the context in which the program is given. The considerations are mostly for developing countries, but include recommendations such as identifying topics specifically aimed for female audiences and addressing the needs of specific subgroups of women. Additionally, Bauer & Dahlquist (1998) suggested that it is best to first acknowledge the existence of gender differences within classrooms and then design financial education programs to include all students.

Among other things, the authors offered suggestions such as using gender-neutral examples in classrooms, eliminating gender bias from exams, and making a conscious effort to call on male and female student equally. If a traditional gender gap in financial knowledge is present, policymakers and educators should take into account what would work best with their own students in order to design effective policies and programs.

7.5 Methodological Implications

Chapter 6 contains information regarding a methodological comparison of multilevel modeling and linear regression models for the PISA 2012 Financial Literacy Assessment. Through the comparisons of model estimates, multilevel models appear to be the best statistical approach to analyzing the PISA data due to its hierarchical nature.[19] The discussion presented below will be limited to examining the differences in fixed effects between the two methodological approaches and two different statistical software packages used for the multilevel modeling estimation.

7.5.1 Fixed Effects

The idea of using fixed effects is found in both the hierarchical linear modeling literature (Garson, 2013; Raudenbush & Bryk, 2002) and the linear regression literature (Clarke et al., 2010; Greene, 2012; Gujarati & Porter, 2009). In multilevel modeling, a fixed effect is analogous to a linear regression estimate (Garson, 20130), while a fixed effect in linear regression allows for the examination of group effects (Gujarati & Porter, 2009). Analyses in Chapter 6 did not fully utilize fixed effects

[19] Detailed analyses of the methodological comparison can be found in Chapter 6.

analyses in linear regression models due to the lack of panel data. To make further comparisons, future analyses should use fixed effects in linear regression to compare the results to multilevel modeling results. The comparisons made in Chapter 6 show a comparison of aggregated linear regression estimates and multilevel modeling with fixed and random effects. Random effects cannot be examined in the context of the linear regression models due to the lack of panel data (Greene, 2012; Dougherty, 2011, as cited in Klawitter, 2012). Future work should focus on more accurately comparing fixed effects in both multilevel models and linear regression models.

7.5.2 Statistical Software for Multilevel Modeling

A variety of statistical software options are present for estimating multilevel models. The two used in this dissertation are SAS® 9.2 and HLM7. Multilevel models in Chapter 4 were estimated using SAS® 9.2, and multilevel models in Chapter 5 were estimated using HLM7. The goal behind the idea of using the two statistical software packages was to compare their estimated results. Using the PROC MIXED procedure in SAS® 9.2, multilevel models are estimated using restricted maximum likelihood as a specific type of generalized linear modeling (GLM) (Sas Institute Inc., 2009). Models outputted produce a mean, or average, model across all groups with fixed effects and covariance parameters (random effects). There are a few downfalls of PROC MIXED: computation time, weighting, and the handling of plausible values. First, models take hours to estimate, which decreases the amount of analyses a researcher can do in a given period of time. SAS® 9.2 also only allows for the root-level weight rather than weights at each level of analysis (Uekawa, 2004). For a two-level multilevel model, this would not be a problem. However, analyses comparing different weighting schemes in Chapter 5 report differences in estimates when using only the root-level weight and when using weights at each level of analysis. Finally, PROC MIXED does not allow for the dependent variable to be a series of plausible values, as is the case with the PISA 2012 data. Results are estimated for each plausible value and then averaged.

The more efficient option is to use HLM 7, which begins estimation by averaging the OLS estimates rather than beginning at value of zero (Garson, 2013). By using HLM 7, results could arguably be more easily compared to linear regression results. Also, from an ease of use standpoint, the HLM 7 software allows for the dependent variable to be a series of plausible values, which expedites the estimation process. It is also the preferred statistical software for many well-known researchers in the field of multilevel modeling (Osborne, 2000; Raudenbush & Bryk, 2002). HLM 7 also allows for the use of weights at each level of analysis, leading to more accurate accounting for differing sample sizes. It should be noted that when estimating the same models with the same data using both SAS® 9.2 and HLM 7, the estimates produced are not the same. In terms of statistical significance, results were similar, but the estimates themselves varied slightly. This could in part be due to the different underlying estimations used by the different statistical packages.

7.6 Limitations

Throughout Chapters 4 – 6, some limitations are discussed. Chapter 4 discusses the limitation presented by the restricted sample, which is less than half the size of the original sample. Also discussed in chapter 4 are the limitations of the parental characteristics, including a lack of information and the issue of self-reported data by students. Chapter 5 is limited by the country-level variables used, in that the variables do not help to explain variance among students across the entire sample. Finally, Chapter 6 discusses the limitations of comparing multilevel modeling with regression analysis. In addition to these and other small limitations, the largest limitation of this dissertation lies in the newness of the data and the methodologies used. The PISA 2012 Financial Literacy Assessment was first administered in 2012, and though it was tested prior to administration, there are discrepancies and noise within the resulting data that could be smoothed out in future administrations. Additionally, while both multilevel modeling and regression analysis have been extensively used before, a comparison of the two methodologies is very rare. Also, there is no statistical test to determine whether or not a multilevel model or linear regression model is the best fit for cross-sectional data. Therefore, future work should seek to find an answer for how to use a statistical test to determine whether or not multilevel modeling is the best methodological approach. The newness of both the dataset and the methodological comparison presented in this dissertation are limiting, but they also make a unique and significant contribution to the financial literacy literature.

REFERENCES

Alhenawi, Y., & Elkhal, K. (2013). Financial literacy of U.S. households : Knowledge vs long-term financial planning. *Financial Services Review*, *22*, 211–244.

Ameriks, J., Leahy, J., & Hall, R. (2003). Wealth accumulation and the propensity to plan. *The Quarterly Journal of Economics*, *118*(3), 1007–1047.

Ammermüller, A., Heijke, H., & Wöβmann, L. (2005). Schooling quality in Eastern Europe: Educational production during transition. *Economics of Education Review*, *24*(5), 579-599.

Asarta, C. J., Hill, A. T, & Meszaros, B. T. (2014). The features and effectiveness of the *Keys to Financial Success* curriculum. *International Review of Economics Education*, *16*(1), 39-50.

Atkinson, A., McKay, S., Collard, S., & Kempson, E. (2007). Levels of financial capability in the UK. *Public Money and Management*, *27*(1), 29–36.

Atkinson, A., & Messy, F. (2012). *Measuring financial literacy*. Organisation for Economic Co-operation and Development.

Avard, S., Manton, E., English, D., & Walker, J. (2005). The financial knowledge of college freshmen. *College Student Journal*, *39*(2), 321–339.

Bauer, R. J., & Dahlquist, J. R. (1999). Recognizing and eliminating gender bias in finance education. *Financial Practice and Education, Spring/Sum*, 83–92.

Becchetti, L., Caiazza, S., & Coviello, D. (2013). Financial education and investment attitudes in high schools: Evidence from a randomized experiment. *Applied Financial Economics*, *23*(April 2015), 817–836.

Behrman, J. R., Mitchell, O.S., Soo, C., & Bravo, D. (2010). Financial literacy, schooling, and wealth accumulation (Working Paper No. 16452). Retrieved from National Bureau of Economic Research website: http://www.nber.org/papers/w16452.

Bell, B. A., Ene, M., Smiley, W., & Schoeneberger, J. (2013). A multilevel model primer using SAS PROC MIXED. In *SAS Global Forum* (p. 1-19).

Bell, B.A., Morgan, G.B., Kromrey, J.D., & Ferron, J.M. (2010). The impact of small cluster size on multilevel models: A Monte Carlo examination of two-level models with binary and continuous predictors. *JSM Proceddings, Survey Research Methods Section,* 4057-4067.

Bell, B.A., Morgan, G.B., Schoeneberger, J.A., Loudermilk, B.L., Kromrey, J.D., & Ferron, J.M. (2010). Dancing the sample size limbo with mixed models: How low can you go. *SAS Global Forum*, *4,* 11-14.

Bernheim, B. D. & Garrett, D. M. (2003). The effects of financial education in the workplace evidence from a survey of households. *Journal of Public Economics*, *87*(7), 1487–1519.

Bernheim, B. D., Skinner, J., & Weinberg, S. (2001). What accounts for the variation in retirement wealth among U.S. households? *American Economic Review*, *91*(4), 832–857.

Borodich, S., Deplazes, S., Kardash, N., & Kovzik, A. (2010). Comparative analysis of the levels of financial literacy among students in the U.S., Belarus, and Japan. *Journal of Economics and Economic Education Research, 11*(3), 71-86.

Bowen, C. F. (2002). Financial knowledge of teens and their parents. *Financial Counseling and Planning*, *13*(2), 93-102.

Boyce, L., & Danes, S. M. (1998). *Evaluation of the NEFE High School Financial Planning Program* ® (pp. 1–39).

Brown, J. R., Ivković, Z., Smith, P. A., & Weisbenner, S. (2008). Neighbors matter : Causal community effects and stock market participation. *American Finance Association*, *63*(3), 1509–1531.

Bruhn, M., Leao, L., Legovini, A., Marchetti, R., & Zia, B. (2013). The impact of high school financial education: Experimental evidence from Brazil. Washington, DC: World Bank Group. Retrieved from : http://documents.worldbank.org/curated/en/2013/12/18640673/ impact-high-school-financial-education-experimental-evidence-brazil.

Butt, N. M., Haessler, S. J., & Schug, M. C. (2008). An incentives-based approach to implementing financial fitness for life in the Milwaukee public schools. *The Journal of Private Enterprise*, *24*(1), 165–173.

Butters, R. B., Asarta, C. J., & McCoy, S. (2012). Financial literacy and gender in U.S. high schools. *Journal of Economics and Finance Education*, *11*(2), 142-149.

Cameron, M. P., Calderwood, R., Cox, A., Lim, S., & Michio, Y. (2013). Personal financial literacy among high school students in New Zealand, Japan and the United States. *Citizenship, Social and Economics Education*, *12*(3), 200–215.

Cameron, M. P., Calderwood, R., Cox, A., Lim, S., & Yamaoka, M. (2014). Factors associated with financial literacy among high school students in New Zealand. *International Review of Economics Education*, *16*, 12–21

Carlin, B.I, & Robinson, D.T. (2012). What does financial literacy training teach us? *The Journal of Economic Education, 43*(3), 235-247.

Chen, H., & Volpe, R. P. (1998). An analysis of personal financial literacy among college students. *Financial Services Review, 7*(2), 107–128.

Chen, H., & Volpe, R. P. (2002). Gender differences in personal financial literacy among college students. *Financial Services Review*, *11*(3), 289–307.

Clarke, P., Crawford, C., Steele, F., & Vignoles, A. F. (2010). The choice between fixed and random effects models: Some considerations for educational research (Working paper 10/240). Retrieved from Centre for Market and Public Organization, Bristol Institute of Public Affairs: http://www.bristol.ac.uk/medialibrary/sites/cmpo/migrated/documents/wp240.pdf

Collins, J. M. (2012). The impacts of mandatory financial education: Evidence from a randomized field study. *Journal of Economic Behavior & Organization*, 1–13.

Cude, B. J., & Kabaci, M. J. (2012). Financial education for college students. In *Consumer knowledge and financial decisions* (pp. 49-66). Springer: New York.

Danes, S.M. (1994). Parental perceptions of children's financial socialization. *Financial Counseling and Planning, 5*(1), 127-149.

Danes, S. (2004). Evaluation of the NEFE high school financial planning program project. Retrieved from https://www.hsfpp.org/Portals/0/Documents/NEFE%20HSFPP%20Impact%20Study%202003-2004.pdf

Deaton, A. (1997). *The analysis of household surveys : A microeconometric approach to development policy*. Baltimore, MD: Published for the World Bank [by] Johns Hopkins University Press.

Denhardt, R. B., & Jeffress, P. W. (1971). Social learning and economic behavior: The process of economic socialization. *American Journal of Economics and Sociology, 30*(2), 113–125.

Dotson, M. J., & Hyatt, E. M. (2005). Major influence factors in children's consumer socialization. *Journal of Consumer Marketing*, *22*(1), 35–42.

Draper, D. (1995). Inference and hierarchical modeling in the social sciences: Implications for research in organizations. *Journal of Management, 24*(5), 623-641.

Dronkers, J., & Robert, P. (2007). Differences in scholastic achievement of public, private government-dependent, and private independent schools: A cross-national analysis. *Educational Policy, 22*(4), 541–577.

Dumouchel, H., & Duncan, G. J. (1983). Using sample survey weights in multiple regression analyses of stratified samples. *Journal of the American Statistical Association*, *78*(383), 535–543.

Edwards, R., Allen, M. W., & Hayhoe, C. R. (2007). Financial attitudes and family communication about students' finances: The role of sex differences. *Communication Reports*, *20*(2), 90–100.

Falahati, L., & Paim, L. (2011). Gender differences in financial well-being among college students. *Australian Journal of Basic and Applies Sciences*, *5*(9), 1765–1776.

Fonseca, R., Mullen, K. J., Zamarro, G., & Zissimopoulos, J. (2012). What explains the gender gap in financial literacy? The role of household decision making. *Journal of Consumer Affairs*, *46*(1), 90–106.

Fuchs, T., & Woessmann, L. (2004). Computer and student learning: Bivariate and multivariate evidence on the availability and use of computers at home and at school (Working Paper No 1321). Retreived from CESifo website: http://www.cesifo-group.de/pls/guestci/download/CESifo%20Working%20Papers%202004/CESifo%20Working%20Papers%20October%202004/cesifo1_wp1321.pdf.

Gale, W. G., & Levine, R. (2010). Financial literacy : What works ? How could it be more effective ? Retrieved from Financial Security Project at Boston College website: http://squaredawayblog.bc.edu/wp-content/uploads/2011/03/FSP-2011-1.pdf.

Garson, G. D. (2013). Fundamentals of hierarchical linear and multilevel modeling. In Garson, G. D. (Ed), *Hierarchical Linear Modeling: Guide and Applications* (3-26). United States: Sage Publishing.

Goldstein, H. (1997). Methods in school effectiveness research. *School Effectiveness and School Improvement*, *8*(4), 369-395.

Gorard, S. (2003). What is multi-level modelling for? *British Journal of Educational Studies*, *51*(1), 46-63.

Greene, W. H. (2012). *Econometric analysis* (7th ed.). Upper Saddle River, N.J.: Prentice Hall.

Grinstein-Weiss, M., Spader, J., Yeong, H. Y., Taylor, A., & Freeze, E. B. (2011). Parental transfer of financial knowledge and later credit outcomes among low- and moderate-income homeowners. *Children and Youth Services Review*, *33*(1), 78–85.

Gujarati, D. N. & Porter, D. C. (2009). *Basic econometrics*. Boston: McGraw-Hill Irwin.

Hancock, A. M., Jorgensen, B. L., & Swanson, M. S. (2013). College students and credit card use: The role of parents, work experience, financial knowledge, and credit card attitudes. *Journal of Family and Economic Issues, 34*(4), 369–381.

Hanushek, E. A. (1979). Conceptual and empirical issues in the estimation of educational production functions. *The Journal of Human Resources, 14*(3), 351–388.

Hanushek, E. A. (1986). The economics of schooling: Production and efficiency in public schools. *Journal of Economic Literature, 24*(3), 1141-1177.

Hanushek, E. A. (1997). Assessing the effects of school resources on student performance : An update. *Educational Evaluation and Policy Analysis*, *19*(2), 141–164.

Harter, C., & Harter, J. (2009). Assessing the effectiveness of *Financial Fitness for Life* in Eastern Kentucky." *Journal of Applied Economics and Policy, 28*(1), 20-33.

Hastings, J. S., Madrian, B. C., & Skimmyhorn, W. L. (2013). Financial literacy, financial education, and economic outcomes. *Annu.Rev.Econ.Annual Review of Economics, 5*(1), 347-373.

Hastings, J. S., & Tejeda-Ashton, L. (2008). Financial literacy, information, and demand elasticity: Survey and experimental evidence from Mexico (Working Paper No. 14538). Retrieved from National Bureau of Economic Research website: http://www.nber.org/papers/w14538.

Hathaway, I., & Khatiwada, S. (2008). Do financial education programs work? (Working Paper 08-03). Retrieved from Federal Reserve Bank of Cleveland website: https://www.clevelandfed.org/en/newsroom-and-events/publications/working-papers/working-papers-archives/2008-working-papers/wp-0803-do-financial-education-programs-work.aspx.

Hedges, L. V. (1994). Does money matter? A meta-analysis of studies of the effects of differential school inputs on student outcomes. *Educational Researcher*, *23*(3), 5-14.

Hilgert, M.A., Hogarth, J. M., & Beverly, S. G. (2003). Household financial management: The connection between knowledge and behavior. *Federal Reserve Bulletin*, 309-322.

Hill, A. T., & Asarta, C.J., (2016). Gender and student achievement in personal finance: Evidence from *Keys to Financial Success.* In Aprea, C., Breuer, K., Davies, P., Fuhrmann, B., Koh, N.K., Lopus, J.S., & E. Wuttke (Eds.), *International Handbook of Financial Literacy* (pp. 545-567). Springer: Singapore.

Hofmann, D. A. (1997). An overview of the logic and rationale of hierarchical linear models. *Journal of Management*, *23*(6), 723–744.

Huang, J., Nam, Y., & Sherraden, M. S. (2013). Financial knowledge and child development account policy: A rest of financial capability. *Journal of Consumer Affairs*, *47*(1), 1–26.

Hung, A. A, Parker, A. M., & Yoong, J. K. (2009). *Defining and measuring financial literacy*. *RAND Corporation Publications Department, Working Papers* (Vol. 708).

Hung, A., Yoong, J., & Brown, E. (2012). Empowering women through financial awareness and education. *OECD Working Papers on Finance, Insurance and Private Pensions*, (14).

Huston, S. J. (2010). Measuring financial literacy. *The Journal of Consumer Affairs, 44*(2), 296–316.

Huta, V. (2014). When to use hierarchial linear modeling. *The Quantitative Methods for Psychology, 10*(1), 13-28.

Jang, K., Hahn, J., & Park, H. J. (2014). Comparison of financial literacy between Korean and U.S. high school students. *International Review of Economics Education, 16*, 22–38.

Jappelli, T. (2010). Economic literacy: An international comparison. *The Economic Journal, 120*(548), F429-F451.

Jappelli, T., & Padula, M. (2013). Investment in financial literacy and saving decisions. *JBF Journal of Banking and Finance, 37*(8), 2779-2792.

Johnson, E., & Sherraden, M. (2007). From financial literacy to financial capability among youth. *Journal of Sociology & Social Welfare*, *34*(3), 119–145.

Jorgensen, B. L., & Savla, J. (2010). Financial literacy of young adults: The importance of parental socialization. *Family Relations, 59*(4), 465-478.

Klapper, L. K., Lusardi, A., & Panos, G. (2012). Financial literacy and the financial crisis (Working Paper No. 17930). Retrieved from National Bureau of Economic Research website: http://www.nber.org/papers/w17930.

Klapper, L., Lusardi, A., & Panos, G. A. (2013). Financial literacy and its consequences: Evidence from russia during the financial crisis. *Journal of Banking & Finance*, *37*(10), 3904-3923.

Klapper, L., Lusardi, A., & van Oudheusden, P. (2015). Financial literacy around the world Insights from the Standard & Poor's ratings services global financial literacy survey. *McGraw Hill Financial.*

Klapper, L. & Panos, G.A. (2011). Financial literacy and retirement planning: the Russian case. *Journal of Pension Economics and Finance*, *10*(4), 599-618.

Klawitter, M. (2012). *Fixed effects and random effects models* [Class handout]. Evans School of Public Affairs, University of Washington, Seattle, WA. Retrieved from http://courses.washington.edu/pbafadv/student%20presentations/Fixed%20Effects,%20Random%20Effects%20Model%20Cheat%20Sheet.pdf.

Kreft, I.G.G. (1996). Are multilevel techniques necessary? An overview, including simulation studies. Unpublished manuscript, California State University at Los Angeles.

Krueger, A. (1999). Experimental estimates of education production functions. *The Quarterly Journal of Economics*, *114*(2), 497-532.

Lachance, M. (2014). Financial literacy and neighborhood effects. *Journal of Consumer Affairs, 48*(2), 251-273.

Lawrence, F.C., Crude, B.J., Lyons, A.C., Marks, L. (2006). College students' financial practices: A mixed methods analysis. *The Journal of Consumer Education*, *23,* 13–26.

Lindley, D.V. & Smith, A.F.M. (1972). Bayes estimates for the linear model. *Journal of the Royal Statistical Society. Series B (Methodological), 34*(1), 1-41.

Lo Prete, A. (2013). Economic literacy, inequality, and financial development. *Economics Letters*, *118*(1), 74-76.

Lührmann, M., Serra-Garcia, M., & Winter, J. (2012). The effects of financial literacy training: Evidence from a field experiment with german high-school children. *Documento De Trabajo De La Universidad De Munich, 201224*

Lusardi, A. (2011). Americans' financial capability (Working Paper No. 17103). Retrieved from National Bureau of Economic Research website: http://www.nber.org/papers/w17103.

Lusardi, A., & Mitchell, O. S. (2007). Financial literacy and retirement preparedness: Evidence and implications for financial education. *Business Economics, 42*(1), 35-44.

Lusardi, A., & Mitchell, O. S. (2008). Planning and financial literacy: How do women fare? *American Economic Review, 98*(2), 413-417.

Lusardi, A., & Mitchell, O. S. (2011). Financial literacy around the world: an overview. *Journal of Pension Economics and Finance, 10*(4), 497–508.

Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature, 52*(1), 5-44.

Lusardi, A., Mitchell, O., & Curto, V. (2010). Financial literacy among the young. *Journal of Consumer Affairs, 44*(2), 358-380.

Maas, C.J.M, & Hox J.J. (2005). Sufficient sample sizes for multilevel modeling. *Methodology, 1*(3), 86-92.

Mahdavi, M., & Horton, N. J. (2014). Financial knowledge among educated women: Room for improvement. *Journal of Consumer Affairs*, *48*(2), 403–417.

Malone, K., Stewart, S. D., Wilson, J., & Korsching, P. F. (2010). Perceptions of financial well-being among American women in diverse families. *Journal of Family and Economic Issues, 31*(1), 63–81.

Mandell, L., & Klein, L. S. (2007). Motivation and financial literacy. *Financial Services Review, 16*(2), 105.

Mandell, L., & Klein, L. S. (2009). The impact of financial literacy education on subsequent financial behavior. *Journal of Financial Counseling and Planning, 20*(1), 15–24.

Manton, E. J., English, D., Avard, S., & Walker, J. (2006). What college freshmen admit to not knowing about personal finance. *Journal of College Teaching & Learning, 3*(1), 43–54.

McNeish, D.M., & Stapleton, L.M. (2016). The effect of small sample size on two-level model estimates: A review and illustration. *Educational Psychology Review, 28*(2), 295-314.

Michaelowa, K. (2001). Primary education quality in francophone Sub-Saharan Africa: Determinants of learning achievement and efficiency considerations. *World Development, 29*(10), 1699-1716.

Moschis, G. P. (1985). The role of family communication in consumer socialization of children and adolescents. *Journal of Consumer Research, 11*(4), 898–913.

Moulton, B. R. (1986). Random group effects and the precision of regression estimates. *Journal of Econometrics, 32*(3), 385-397.

Newcomb, M. D., & Rabow, J. (1999). Gender, socialization, and money. *Journal of Applied Social Psychology, 29*(4), 852–869.

Newsom, J. (2015). *Distinguishing between random and fixed: Variables, effects, and coefficients* [Class Handout]. School of Community Health, Portland State University, Portland, OR. Retrieved from http://web.pdx.edu/~g3jn/mlrclass/ho_randfixd.doc.

Nicholson, W., & Snyder, C. (2012). *Microeconomic theory: Basic principles and extensions*. Mason, Ohio: South-Western/Cengage Learning.

Nicolini, G., Cude, B. J., & Chatterjee, S. (2013). Financial literacy: A comparative study across four countries. *International Journal of Consumer Studies, 37*(6), 689–705.

Norvilitis, J. M., & MacLean, M. G. (2010). The role of parents in college students' financial behaviors and attitudes. *Journal of Economic Psychology*, *31*(1), 55–63.

Organisation for Economic Co-operation and Development. (2009). *PISA Data Analysis Manual: SAS, Second Edition*, PISA, OECD Publishing, Paris.

Organisation for Economic Co-operation and Development. (2013a). *PISA 2012 assessment and analytical framework mathematics, reading, science, problem solving and financial literacy*. Paris: OECD Publishing.

Organisation for Economic Co-operation and Development. (2013b). *Women and financial education : Evidence, policy responses and guidance.* Paris: OECD Publishing.

Organisation for Economic Co-operation and Development. (2014a). PISA 2012 results: Students and money (volume VI) financial literacy skills for the 21st century.

Organisation for Economic Co-operation and Development. (2014b). *PISA 2012 technical report*. Paris: OECD Publishing.

Orton, L. (2007). *Financial literacy: Lessons from international experience.* Retrieved from Canadian Policy Research Networks website: http://canlearnsociety.ca/wp-content/uploads/2013/01/Financial-Literacy-Lessons-from-International-Experience.pdf.

Osborne, J.W. (2000). Advantages of hierarchical linear modeling. *Practical Assessment, Research & Evaluation,* 7(1), 1-3.

Osborne, J.W., & Neupert, S.D. (2013). A brief introduction to hierarchical linear modeling. In T. Teo (Ed), *Handbook of Quantitiatve Methods for Educational Research* (pp. 187-198). Rotterdam: Sense Publishers.

Peng, T., Bartholomae, S., Fox, J., & Cravener, G. (2007). The impact of personal finance education delivered in high school and college courses. *Journal of Family and Economic Issues, 28*(2), 265-284.

Pfeffermann, D. (1993). The role of sampling weights when modeling survey data. *International Statistical Review/ Revue Internationale de Statistique, 61*(2), 317-337.

Raudenbush, S., & Bryk, A. (2002). *Hierarchical linear models: Applications and data analysis methods*. Thousand Oaks: Sage Publications.

Remund, D. L. (2010). Financial literacy explicated: The case for a clearer definition in an increasingly complex economy. *Journal of Consumer Affairs*, *44*(2), 276–295.

Robb, C.A. & Sharpe, D.L. (2009). Effect of personal financial knowledge on college students' credit card behavior. *Journal of Financial Counseling and Planning, 20*(1), 25-43.

Rothstein, J. (2010). Teacher quality in educational production: Tracking, decay, and student achievement. *Quarterly Journal of Economics, 125*(1), 175-214.

Schmeiser, M. D., & Seligman, J. S. (2013). Using the right yardstick: Assessing financial literacy measures by way of financial well-being. *Journal of Consumer Affairs, 47*(2), 243–262.

Schmidt, W. H., Cogan, L., & Houang, R. (2011). The role of opportunity to learn in teacher preparation: An international context. *Journal of Teacher Education, 62*(2), 138-153.

Schütz, G. (2009). Does the quality of pre-primary education pay off in secondary school? An international comparison using PISA 2003. (IFO Working Paper, No. 68). Retrieved from: http://econpapers.repec.org/paper/cesifowps/_5f68.htm.

Snijders, T.A.B. (2005). Power and sample size in multilevel modeling. In B.S. Everitt & D.C. Howell (Eds.), *Encyclopedia of Statistics in Behavioral Science, Volume 3* (pp. 1570-1573). Chicester: Wiley.

Sohn, S. H., Joo, S. H., Grable, J. E., Lee, S., & Kim, M. (2012). Adolescents' financial literacy: The role of financial socialization agents, financial experiences, and money attitudes in shaping financial literacy among South Korean youth. *Journal of Adolescence, 35*(4), 969–980.

Steenbergen, M.R. & Jones, B. S. (2002). Modeling multilevel data structures. *American Journal of Political Science, 46*(1), 218-237.

Tennyson, S., & Nguyen, C. (2001). State curriculum mandates and student knowledge of personal finance. *Journal of Consumer Affairs, 35*(2), 241-62.

Uekawa, K. (2004). *Doing HLM by SAS® PROC MIXED.* Retrieved from http://www.estat.us/sas/PROCMIXED.doc

Van Campenhout, G. (2015). Revaluing the role of parents as financial socialization agents in youth financial literacy programs. *The Journal of Consumer Affairs, 49*(1), 186-222.

van Rooij, M. C. J., Lusardi, A., & Alessie, R. J. M. (2012). Financial literacy, retirement planning and household wealth. *The Economic Journal, 122*(560), 449-478.

Varcoe, K. P., Martin, A., Devitto, Z., & Go, C. (2005). Using a financial education curriculum for teens. *Journal of Financial Counseling and Planning, 16*(1), 63-71.

Wagner, J. (2015). *An analysis of the effects of financial education on financial literacy and financial behavior* (Doctoral dissertation). Retrieved from http://digitalcommons.unl.edu/cgi/viewcontent.cgi?article=1054&context=businessdiss.

Walstad, W. B., Rebeck, K., & MacDonald, R. A. (2010). The effects of financial education on the financial knowledge of high school students. *Journal of Consumer Affairs, 44*(2), 336-357.

Ward, S. (1974). Consumer socialization. *Journal of Consumer Research, 1*(2), 1–14.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedastiticy. *Econometrica, 48*(4), 817–838.

Widdowson, D., & Hailwood, K. (2007). Financial literacy and its role in promoting a sound financial system. *Reserve Bank of New Zealand Bulletin, 70*(2), 37-47.

Woltman, H., Feldstain, A., MacKay, J.C., & Rocchi, M. (2012). An introduction to hierarchial linear modeling. *Tutorials in Quantitiative Methods for Psychology,* 8(1), 52-69.

Wooldridge, J. M. (2001). Asymptotic properties of weights M-estimators for standard stratified samples. *Econometric Theory, 17*(2), 451–470.

Worthington, A. C. (2006). Predicting financial literacy in Australia. *Financial Services Review, 15*(1), 59–79.

Xiao, J. J. & O'Neill, B. (2016). Consumer financial education and financial capability. *International Journal of Consumer Studies.* Advance online publication.

Appendix A

2004 US HEALTH AND RETIREMENT SURVEY FINANCIAL LITERACY QUESTIONS

1. *Suppose you have $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?* More than $102 Exactly $102 Less than $102 Do not know Refuse to Answer
2. *Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?* More than today Exactly the same Less than today Do not know Refuse to Answer
3. *Please tell me whether this statement is true of false. 'Buying a single company's stock usually provides a safer return than a stock mutual fund.'* True False Do not know Refuse to Answer

Note: Questions were provided by Lusardi & Mitchell (2011).

Appendix B

FINANCIAL LITERACY ASSESSMENT QUESTION DETAILS, PISA 2012

Table B.1 Financial Literacy Assessment Question Details, PISA 2012

Variable	Name	Item Form	Content	Process	Context	Cluster	% Correct
PF001Q01	Costs of Running a Car	Multiple Choice	Planning	Analyze information in financial context	Home & Family	PF1	74.81
PF004Q03	Income Tax	Constructed Response	Planning	Evaluate financial issues	Education & Work	PF2	6.98
PF006Q02	Music System	Multiple Choice	Planning	Analyze information in financial context	Individual	PF2	57.67
PF009Q02	Shopping	Multiple Choice	Money	Apply financial knowledge and understanding	Home & Family	PF1, PFUH	93.17
PF010Q01	Bank statement	Constructed Response	Money	Identify financial information	Home & Family	PF1	50.40
PF010Q02	Bank statement	Constructed Response	Money	Analyze information in financial context	Home & Family	PF1	25.59
PF012Q01	Interest	Multiple Choice	RiskReward	Apply financial knowledge and understanding	Individual	PF1	60.74
PF012Q02	Interest	Multiple Choice	RiskReward	Analyze information in financial context	Individual	PF1	47.56
PF024Q02	Jacket Sale	Constructed Response	Money	Evaluate financial issues	Individual	PF2	62.54
PF028Q02	Phone plans	Constructed Response	Planning	Analyze information in financial context	Individual	PF1, PFUH	59.00
PF028Q03	Phone plans	Multiple Choice	Planning	Analyze information in financial context	Individual	PF1, PFUH	74.90

Table B.1 continued

PF031Q01	Laptop	Multiple Choice	RiskReward	Evaluate financial issues	Home & Family	PF1, PFUH	29.08
PF031Q02	Laptop	Constructed Response	RiskReward	Apply financial knowledge and understanding	Home & Family	PF1, PFUH	56.47
PF033Q01	Wayne’s Bank Statement	Multiple Choice	Money	Analyze information in financial context	Individual	PF2, PFUH	37.75
PF033Q02	Wayne’s Bank Statement	Multiple Choice	Money	Identify financial information	Individual	PF2, PFUH	58.62
PF035Q01	Ringtones	Constructed Response	Landscape	Apply financial knowledge and understanding	Individual	PF2, PFUH	53.39
PF036Q01	Online Shopping	Constructed Response	Landscape	Evaluate financial issues	Societal	PF1	46.80
PF051Q01	Bicycle Shopping	Constructed Response	Planning	Evaluate financial issues	Education & Work	PF2	83.66
PF051Q02	Bicycle Shopping	Constructed Response	Planning	Evaluate financial issues	Education & Work	PF2	48.85
PF052Q01	Video Game	Multiple Choice	Planning	Identify financial information	Individual	PF2	76.92
PF054Q01	E-mail	Constructed Response	Landscape	Evaluate financial issues	Societal	PF1	66.79
PF055Q03	Invoice	Constructed Response	Money	Apply financial knowledge and understanding	Individual	PF2	37.58
PF058Q01	Personal Identification Number	Constructed Response	RiskReward	Evaluate financial issues	Societal	PF2, PFUH	86.55
PF062Q01	Mobile Phone Contract	Multiple Choice	Landscape	Evaluate financial issues	Home & Family	PF2, PFUH	75.64
PF068Q01	Job Change	Constructed Response	Planning	Evaluate financial issues	Education & Work	PF1	52.51
PF069Q01	Student Account	Multiple Choice	Landscape	Analyze information in financial context	Education & Work	PF2	69.53
PF075Q02	Study Options	Multiple Choice	Planning	Analyze information in financial context	Education & Work	PF2	31.07
PF082Q01	New Bike	Constructed Response	Money	Identify financial information	Individual	PF1	65.93
PF082Q02	New Bike	Multiple Choice	RiskReward	Identify financial information	Home & Family	PF1	83.96

Table B.1 continued

PF095Q01	Changing Value	Multiple Choice	Money	Identify financial information	Home & Family	PF2	33.17
PF095Q02	Changing Value	Multiple Choice	Landscape	Analyze information in financial context	Societal	PF2	28.03
PF097Q01	Company Profit	Multiple Choice	Landscape	Identify financial information	Individual	PF1	11.27
PF102Q01	Gantica	Constructed Response	RiskReward	Apply financial knowledge and understanding	Home & Family	PF2, PFUH	85.51
PF102Q02	Gantica	Constructed Response	RiskReward	Apply financial knowledge and understanding	Home & Family	PF2, PFUH	65.43
PF103Q01	Investing	Constructed Response	RiskReward	Evaluate financial issues	Individual	PF1	32.25
PF105Q01	Interest Rates	Multiple Choice	Money	Apply financial knowledge and understanding	Individual	PF1, PFUH	33.46
PF105Q02	Interest Rates	Multiple Choice	Money	Apply financial knowledge and understanding	Individual	PF1, PFUH	42.99
PF106Q01	Family Holiday	Constructed Response	Planning	Evaluate financial issues	Home & Family	PF2, PFUH	77.05
PF106Q02	Family Holiday	Multiple Choice	Planning	Apply financial knowledge and understanding	Home & Family	PF2, PFUH	54.87
PF110Q01	Living Alone	Multiple Choice	Planning	Evaluate financial issues	Home & Family	PF1, PFUH	90.91

Table B.2 Financial Literacy Assessment Questions by Content Area, PISA 2012

Content	Question(s)	% of questions	Average % Correct (n=29,041)
Planning	PF001Q01, PF004Q03, PF006Q02, PF028Q02, PF028Q03, PF051Q01, PF051Q02, PF052Q01, PF068Q01, PF075Q02, PF106Q01, PF106Q02, PF110Q01	32.5%	60.71%
Money	PF009Q02, PF010Q01, PF010Q02, PF024Q02, PF033Q01, PF033Q02, PF055Q03, PF082Q01, PF095Q01, PF105Q01, PF105Q02	27.5%	49.20%
RiskReward	PF012Q01, PF012Q02, PF031Q01, PF031Q02, PF058Q01, PF082Q02, PF102Q01, PF102Q02, PF103Q01	22.5%	60.84%
Landscape	PF0W35Q01, PF036Q01, PF054Q01, PF069Q01, PF095Q02, PF097Q01	17.5%	31.95%

Table B.3 Financial Literacy Assessment Questions by Process, PISA 2012

Process	Question(s)	% of questions	Average % Correct (n=29,041)
Analyze information in financial context	PF001Q01, PF006Q02, PF010Q02, PF012Q02, PF028Q02, PF028Q03, PF033Q01, PF069Q01, PF075Q02, PF095Q02	25.00%	50.59%
Evaluate financial issues	PF004Q03, PF024Q02, PF031Q01, PF036Q01, PF051Q01, PF051Q02, PF058Q01, PF062Q01, PF068Q01, PF103Q01, PF106Q01, PF110Q01	30.00%	63.30%
Apply financial knowledge and understanding	PF009Q02, PF012Q01, PF031Q02, PF035Q01, PF055Q03, PF102Q01, PF102Q02, PF105Q01, PF105Q02, PF106Q02	25.00%	58.36%
Identify financial information	PF010Q01, PF033Q02, PF052Q01, PF082Q01, PF082Q02, PF095Q01, PF095Q02, PF097Q01	20.00%	47.53%

Table B.4 Financial Literacy Assessment Questions by Context, PISA 2012

Context	Question(s)	% of questions	Average % Correct (n=29,041)
Home & Family	PF001Q01, PF009Q02, PF010Q01, PF010Q02, PF031Q01, PF031Q02, PF062Q01, PF082Q02, PF095Q01, PF102Q01, PF102Q02, PF106Q01, PF106Q02, PF110Q01	35.00%	60.71%
Education & Work	PF004Q03, PF051Q01, PF051Q02, PF068Q01, PF069Q01, PF075Q02	15.00%	48.77%
Individual	PF006Q02, PF012Q01, PF012Q02, PF024Q02, PF028Q02, PF028Q03, PF033Q01, PF033Q02, PF035Q01, PF052Q01, PF055Q03, PF082Q01, PF097Q01, PF103Q01, PF105Q01, PF105Q02	40.00%	50.79%
Societal	PF036Q01, PF054Q01, PF058Q01, PF095Q02	10.00%	64.00%

Appendix C

SAMPLE QUESTIONS, PISA 2012

Sample Question 1

INVOICE

Sarah receives this invoice in the mail.

BC

Breezy Clothing

Invoice
Invoice Number: 2034
Date issued: 28 February

Sarah Johanson
29 Worthill Rd
Kensington
Zedland 3122

Breezy Clothing
498 Marple Lane
Brightwell
Zedland 2090

Product code	Description	Quantity	Unit cost	Total (excluding tax)
T011	T-shirt	3	20	60 zeds
J023	jeans	1	60	60 zeds
S002	scarf	1	10	10 zeds

Total Excluding Tax:	130 zeds
Tax 10%:	13 zeds
Postage:	10 zeds
Total Including Tax:	153 zeds
Already Paid:	0 zeds
Total due:	153 zeds
Date due:	31 March

INVOICE – ***QUESTION 1***

Why was this invoice sent to Sarah?

A. Because Sarah needs to pay the money to Breezy Clothing.
B. Because Breezy Clothing needs to pay the money to Sarah.
C. Because Sarah has paid the money to Breezy Clothing.
D. Because Breezy Clothing has paid the money to Sarah.

Question Type: Multiple choice
Description: Recognize the purpose of an invoice

Content: Money and transactions
Process: Identify financial information
Context: Individual
Difficulty: Level 1
Correct Answer: A

<u>Sample Question 2</u>

INVOICE – *QUESTION 2*

How much has Breezy Clothing charged for delivering the clothes?

Delivery charge in zeds: ………………..…………………..………………..

Question Type: Constructed response
Description: Identify the cost of postage on an invoice
Content: Money and transactions
Process: Identify financial information
Context: Index
Difficulty: Level 2
Correct Answer: 10 or ten

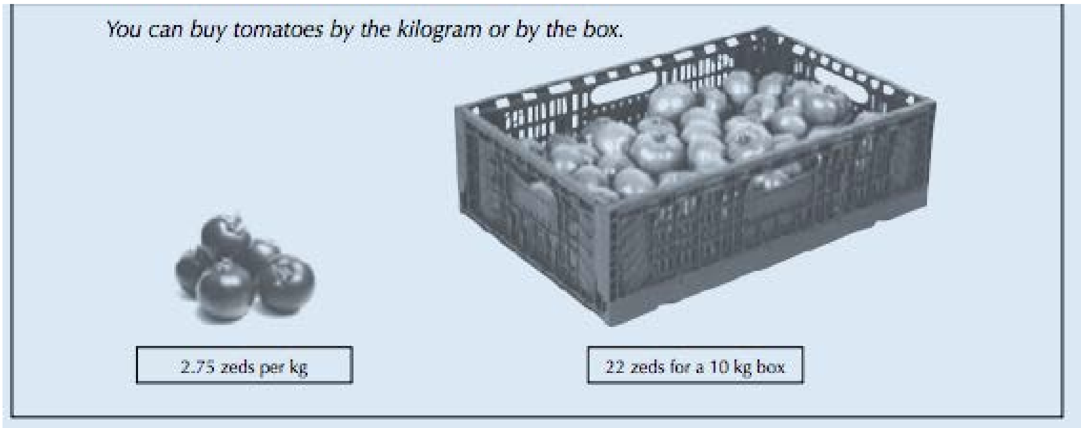
<u>Sample Question 3</u>

INVOICE – *QUESTION 3*

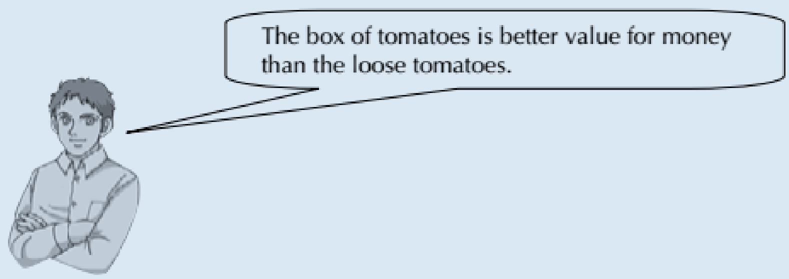
Sarah notices that Breezy Clothing made a mistake on the invoice.
Sarah ordered and received two T-shirts, not three.
The postage fee is a fixed charge.
What will be the total on the new invoice?

Question Type: Constructed response
Description: Find a new total on an invoice
Content: Money and transactions
Process: Apply financial knowledge and understanding
Context: Individual
Difficulty: Full credit – Level 5; Partial Credit – Level 3
Correct Answer: 131 (Full Credit); 133, 121 (partial credit)

Sample Question 4



AT THE MARKET – *QUESTION 2*



Give a reason to support this statement.

....

....

Question Type: Constructed response
Description: Recognize value by comparing prices per unit
Content: Money and transactions
Process: Analyze information in a financial context
Context: Home and family
Difficulty: Level 2
Correct Answer: Answer much recognize that the price per kg of boxed tomatoes is less than the price per kg for loose tomatoes

Sample Question 5

AT THE MARKET – *QUESTION 3*

Buying a box of tomatoes may be a bad financial decision for some people.
Explain why.

....

....

Question Type: Open-constructed response
Description: Recognize value by comparing prices per unit
Content: Money and transactions
Process: Evaluate financial issues
Context: Home and Family
Difficulty: Level 1
Correct Answer: Answers will vary. Should include something about wastage and/or some cannot afford tomatoes.

Sample Question 6

NEW OFFER

Mrs Jones has a loan of 8 000 zeds with FirstZed Finance. The annual interest rate on the loan is 15%. Her repayments each month are 150 zeds.

After one year Mrs Jones still owes 7 400 zeds.

Another finance company called Zedbest will give Mrs Jones a loan of 10 000 zeds with an annual interest rate of 13%. Her repayments each month would also be 150 zeds.

NEW OFFER – *QUESTION 1*

If she takes the Zedbest loan, Mrs Jones will immediately pay off her existing loan.
What are two other *financial* benefits for Mrs Jones if she takes the Zedbest loan?

1. ....

2. ....

Question Type: Constructed response
Description: Recognize positive consequences of transferring a loan

Content: Planning and managing finances
Process: Analyze information in a financial context
Context: Individual
Difficulty: Full credit – Level 5; Partial Credit – Level 3
Correct Answer: Full credit – answer refers to both having extra money and getting a lower interest rate; Partial credit – answer refers to either having extra money or getting a lower interest rate

Sample Question 7

NEW OFFER – *QUESTION 2*

What is one possible *negative* financial consequence for Mrs Jones if she agrees to the Zedbest loan?

....

Question type: *Constructed response*
Description: *Recognise a negative consequence of having a large loan*
Content: *Planning and managing finances*
Process: *Evaluate financial issues*
Context: *Individual*
Difficulty: *582 (Level 4)*

Question Type: Constructed response
Description: Recognize a negative consequence of having a large loan
Content: Planning and managing finances
Process: Evaluate financial issues
Context: Individual
Difficulty: Level 4
Correct Answer: Answer discusses aspects like more debt, more interest, longer to pay

Sample Question 8

PAY SLIP

Each month, Jane's salary is paid into her bank account. This is Jane's pay slip for July.

EMPLOYEE PAY SLIP: Jane Citizen	
Position: Manager	1 July to 31 July
Gross salary	2 800 zeds
Deductions	300 zeds
Net salary	2 500 zeds
Gross salary to date this year	19 600 zeds

PAY SLIP – *QUESTION 1*

How much money did Jane's employer pay into her bank account on 31 July?

A. 300 zeds

B. 2 500 zeds

C. 2 800 zeds

D. 19 600 zeds

Question Type: Multiple choice
Description: Identify the net salary on a pay slip
Content: Money and transactions
Process: Identify financial information
Context: Education and work
Difficulty: Level 4
Correct Answer: B

Note: Questions and supporting information adapted from OECD (2014a).

Appendix D

SELECTED SOURCES FOR PARENTS TO TEACH CHILDREN ABOUT FINANCIAL MATTERS

Organization	Information	Website (As of July 2016)
National Endowment for Financial Education	-Age specific goals -Additional links to terms and activities	http://www.smartaboutmoney.org/Your-Money/Life-Transitions/Talk-to-Your-Kids-About-Finances
American Institute of CPAs	-Links to articles about financial concepts -Content ranging from saving early to stocks	http://www.360financialliteracy.org/Topics/Family-Financial-Planning/How-to-Talk-to-Your-Children-About-Money
Morgan Stanley	-10 "rules" for talking to children about money -"Rules" range from repeating information often to practicing what you tell your kids	https://www.morganstanley.com/wealth/wealthplanning/pdfs/talktokidsaboutmoney.pdf
Charles Schwab	-Has rules and guidelines to follow -Contains activities for parents and kids as well as educational resources	http://www.schwabmoneywise.com/public/moneywise/parents_educators/money_basics
Utah State Office of Education	-Contains a list of books to teach kids about money	http://financeintheclassroom.org/parent/books.shtml
Federal Reserve Education	-Lesson plans to accompany children's literature books on financial concepts	https://www.federalreserveeducation.org/