An Investigation of International Science Achievement Using the OECD's PISA 2006 Data Set

by

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Abstract

School Effectiveness Research (SER) is concerned with efforts to better understand the effectiveness enhancing relationship between student and school variables and how these variables primarily influence academic achievement (Scheerens, 2004). However, one identified methodological shortcoming in SER is the absence of cross-cultural perspectives (Kyriakides, 2006). This is a concern as what may prove effective in one nation does not necessarily mean that it can be easily and seamlessly imported into another with the same results. This study looked at the relationships between science self-beliefs and academic achievement in science across all nations who participated in the Programme for International Student Assessment (PISA) in 2006. It further explored the variance accounted for by cultural, social and economic capital (the elements of the PISA socioeconomic status variable) for each country in PISA 2006 when predicting scientific literacy. Lastly, it used hierarchical linear modeling (HLM) to analyze data from PISA 2006 for nations experiencing high rates of immigration (i.e., Germany, Spain, Canada, the United States, Australia and New Zealand). The outcome measures used for these countries were achievement scores in science, mathematics and reading. The variables examined at the student level were science self-efficacy, science self-concept, immigrant status and socioeconomic status. The variables examined at the school level were student level aggregates of school proportion of immigrants and school socioeconomic status. In the correlation analysis between science literacy and either science self-concept of science self-efficacy, findings suggest

that at the student level, students with both higher science self-concept and higher science self-efficacy tend to achieve higher academically. However, at the country level the relationship was negative between self-concept and academic achievement in science (i.e., countries with higher science self-concept tend to achieve lower on scientific literacy). When the variables that comprised each of the cultural, social, and economic components of SES were regressed on scientific literacy for the PISA sample, cultural capital accounted for 16% of the variance in scientific literacy scores compared to 14% for social capital, 13% for the composite Economic Social and Cultural Status (ESCS), and 12% for economic capital. In the HLM null models, the intraclass correlations for the all countries except for Germany ranged from .16 to .29 (Germany's was between .57 and .68). In the final models, at level-1 country, immigrant status tended to negatively influence achievement (i.e., non-native students are predicted to have lower performance), while science self-efficacy and science self-concept positively influenced achievement. The student level ESCS variable also impacted achievement positively. At the school level, level-2, school mean ESCS or school proportion of immigrants were found to significantly influence the level-1 predictors; however, a good deal of variability across nations was observed. The findings from this study demonstrate that there are some distinct national differences in the relationships between science self-beliefs, immigrant status and academic achievement.

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Chapter 1: Introduction

The theoretical perspective that proposes that student background characteristics are more important to academic success than school characteristics is generally linked to the work of Coleman, Campbell, Hobson, McPartland, Mood, Winfield, and York (1966) and Jencks, Smith, Acland, Bane, Cohen, Gintis, Heyns, and Michelson (1972). These studies came to similar conclusions regarding the amount of variance that can be explained by educational factors. After taking into account student background characteristics (e.g., ability and family background), little variance in student achievement remained (Creemers, 2006). These theories propose heterogeneity of student responses to school characteristics.

As a direct response to this theoretical perspective, the first studies in school effectiveness research (SER)—initially published in the 1970s—emerged through the works of George Weber and Ron Edmonds (Raptis & Fleming, 2003). These studies received a great deal of public attention as they demonstrated that schools and education could make a considerable difference in children's lives. One of the central theoretical assumptions of school effectiveness research is that specific school attributes are associated with academic achievement. SER argues that the effects of schools on academic achievement have been neglected and proposes that even when social and other student factors are taken into account, substantive differences in student performance among schools remain, which can be ascribed to the quality of the schooling itself (Goldstein & Woodhouse, 2000). A major proposition of this framework is that schools are the foremost factor influencing academic success, and the way to improve student outcomes is to identify and reproduce characteristics of good schools. An implicit assumption in this framework is that students are relatively homogeneous and respond equally to school characteristics.

These two perspectives provide conflicting assumptions about the major influences on

student achievement. To help build an understanding of the relationship between student and school variables, this dissertation will make use of a large sample of students from nations around the world to compare the relative importance of student and school influences on academic achievement.

Objectives of the Study

After more than three decades, some researchers have expressed concerns regarding the theoretical assumptions of SER and the methodology employed (Elliot, 1996; Kyriakides, 2006). These concerns can be grouped into four categories: (a) governmental abuse, (b) oversimplification of the complex causalities associated with education, (c) empirical validation driving theory development, and (d) the poor quality of the research in general (Goldstein & Woodhouse, 2000). As a response to these concerns, the field of SER has called for the employment of longitudinal design, advanced statistical techniques to capture the multilevel nature of school effectiveness, and the expansion of studies from the traditional ethnocentric approach to a more cross-national one (Creemers, 2006).

The absence of cross-national perspectives and relationships in educational effectiveness is concerning because ethnocentric studies lead to simplistic suggestions for raising standards based upon the transplanting of knowledge from one country to another (Creemers, 2006; Kyriakides, 2006a). Factors that appear to work in one country cannot be assumed to work in another. Additionally, the range of school and teacher influence is assumed to be smaller within a country than when between-country variation is explored (Kyriakides, 2006). For example, Kyriakides (2006a) showed that in Cyprus and the Netherlands less than 50% of variance at the student level is attributable to schools and teachers for mathematics with data from the Third International Mathematics and Science Study (TIMSS) compared to 60% in most national

effectiveness studies. Finally, SER could gain considerable benefits from an international expansion as comparative studies are more likely to generate more sensitive theoretical explanations than are currently available (Creemers, 2006). Kyriakides (2006a) further argues that these models reveal the importance of conducting comparative studies in order to identify direct and indirect effects of factors upon student achievement at the context/national level. Planners, funders, and consumers of education are expressing interest in international and comparative studies as they seek ways of dealing with the implications of competitive league tables, market forces, multiple innovations, and demands for ever more cost-effective ways of increasing access and improving the quality of educational provision (Crossley & Watson, 2003).

The research in this dissertation informs and builds on cross-cultural comparative theory by examining if differences in academic achievement are associated more with individual student or school membership. Thus, the examination of whether or not students are homogenous within schools and, if not, which differences in background are significant will be useful in understanding variation in student outcomes. This thesis focuses on: (a) the relationship between select student background factors and academic achievement for all nations that participated in the Programme for International Student Assessment (PISA) 2006 study, (b) the estimation of variance components at the student and school level for six nations of high immigration in the PISA 2006 data set, and (c) the subsequent identification of select factors that further account for the student and school variance in academic achievement across these six nations.

Importance of the Study

There are a number of reasons why this study is important in the development of cross-cultural theory and practice in school effectiveness research. Firstly, the migration of people from one nation to another between 1990 and 2000 reached an all-time high of 2.6 million annually

and is projected to average 2.2 million for the next 50 years (United Nations Department of Economic and Social Affairs/Population Division [UN], 2006). This increase has given rise to a greater research emphasis on understanding the heterogeneity of immigrant academic achievement (e.g., Ammermueler, 2007; Entorf & Minoiu 2004; Huang 2000; Marks 2005). A nation's school system plays a critical role in educating immigrant children and facilitating their participation in the larger society (Huang, 2000). However, numerous studies have documented lower achievement for immigrant students compared to non-immigrant students on international academic assessments (Huang, 2000; Leung, 2002; Marks, 2005). Additional studies have uncovered reasons for these lower results in immigrant academic achievement, including differing levels of socio-economic status (SES), home background, and motivation (Blair & Qian, 1998; Fuligni, 1997). A key objective is to understand and explore student academic achievement in the framework of these background variables across nations of high immigration.

Additionally, large datasets such as PISA developed by the Organization for Economic Cooperation and Development (OECD) can be utilized to help uncover what works and what does not work for students. Studies such as PISA have demonstrated sizable variations in educational outcomes (i.e., reading, mathematics, and science) between countries. Consistently, countries such as Canada, Finland, Japan, Singapore, and South Korea rate much better on academic outcome measures than the other countries, and the same countries consistently come out ahead in the rankings regardless of the domain measured ("How to be on top", 2007). However, the achievement scores from programs such as PISA typically provide limited information, due either to the way they are interpreted or the way the results are disseminated.

According to Anderson, Rogers, Klinger, Ungerleider, Glickman, and Anderson (2006, p. 707), "The publication of these rankings implies that variation in student performance is solely

due to school effects". Simple rankings of nations compared to the OECD mean score (see http://www.pisa.oecd.org)—known as the *league tables*—fail to account for the contextual relationships of scores to background traits of the students, schools, or communities. In part due to the over-reporting of testing results in the form of simple rankings as well as a lack of interest in or attention to the varied contexts within which schooling occurs, serious limitations have been identified regarding previous studies' attempts to uncover what works and what does not work in educational effectiveness (Teddlie, Stingfield, & Reynolds, 2000).

Ancillary to the usefulness of large international databases such as PISA is the recognition that science literacy is one of the three domains measured (along with mathematical literacy and reading literacy). In our current technologically based society, an understanding of fundamental scientific concepts and theories and how this can be applied to the challenges we face collectively is more important than ever (OECD, 2006). Mathematics and science preparation is linked to future needs (Wang, 1998), and no nation can afford poor academic achievement or high dropout rates among its young people without jeopardizing its economic future (Raptis & Fleming, 2003). Hanushek, Jameson, Jameson, and Woessmann (2008) used a country's performance on international tests of mathematics and science, as measured through cognitive skills, to demonstrate that those countries with higher test scores experienced far higher economic growth rates on the order of 10% of gross domestic product (GDP) over the last half century.

In this thesis, it is argued that one possible approach to understanding more about why some variables explain effectiveness across countries while others do not is through the use of multilevel educational effectiveness models by conducting secondary analyses of data from international comparative studies. If patterns of significant student-level and school-level

variables are relatively stable across countries, then we expect few differences in how school systems support students. However, if differences exist in how student achievement is supported across national school systems, then we expect these differences to emerge in the final models.

Chapter 2: Review of the Literature

Beaton, Postlewaite, Ross, Spearritt, and Wolf (1999) suggest that there are many attributes of studies such as PISA that can be of great benefit to national policy makers in education. Additionally, the development of more sophisticated statistical techniques (i.e., multilevel models) has allowed researchers to better account for differences in student body characteristics between schools, such as whether some schools are more or less effective for particular student demographics (e.g., male/female, ethnic groups, SES) (Sammons, Hillman, & Mortimer, 1995). This chapter discusses school effectiveness research, scientific literacy, theory and research on science education, and provides a framework for the inclusion of the student-level and school-level variables selected for analysis in this study. Although the study focuses on student and school contextual background variables (i.e., immigrant and socioeconomic status), some additional student climate variables (i.e., science self-beliefs) are also included in the literature review and subsequent models. Traditionally, school effects research focuses on the climate variables as they are under direct control of the teachers, administrators, and parents and potentially malleable to policy. However, the contextual variables are of interest here as the effects of school climate may be adjusted for school context (O'Connell & McCoach, 2008).

School Effectiveness Research

Educational theory has traditionally argued that the major factors of influence upon student attainment are physiological and socio-cultural (SAEE, 2000). However, those who favour the ideas of school effectiveness believe that school characteristics and practices affect

student achievement. This is not to say that student characteristics do not have an effect on student outcomes, but that practices exist (at the national, district, school, and classroom levels) that improve the outcomes of those students who are expected to not achieve the same results as peers with more academically beneficial characteristics. The ideas of SER, as well as the international assessments and important contextual variables that they seek to measure, will be explored more fully here.

School Effectiveness

In attempts to uncover what makes a school successful, the term *effective* is often associated with some measure of the quality of education (Scheerens & Bosker, 1997). SER investigates performance differences—as measured by student achievement—between and within schools, as well as those factors that can enhance school performance (Luyten, Visscher, & Witziers, 2005). The first studies in SER—initially published in the 1970s—began with the works of George Weber and Ron Edmonds (Raptis & Fleming, 2003). The influence of schools, teachers, and education on student achievement had been neglected in research to that time. Early SER researchers argued that even when social and other background factors were taken into account (i.e., statistically controlled), differences among schools remained that could be connected to the quality of those schools (Goldstein & Woodhouse, 2000).

The central theoretical assumption behind SER is that schools can and do have an effect on the achievement of their students. Attempts to operationalize these effects have identified a successful school as one that takes students further academically compared to others with similar student populations (Sammons et al., 1995). Essentially, this amounts to inter-individual comparison to other schools with similar student composition. A considerable research body exists to document evidence that, despite the influence of ability and environmental factors,

schools in similar social circumstances can achieve very different levels of educational progress (e.g., Willms & Raudenbush, 1989).

Concerns. However, despite the recognition of what makes an effective school, the identification of associated and influential factors appears easier than the application of this knowledge toward making schools more effective. A small number of key characteristics of effective schools are promoted to initiate improvements—simple solutions within a framework of crude social engineering (Goldstein & Woodhouse, 2000). This interpretation of SER presents simplistic-sounding solutions (i.e., list of key factors that lead to school success) that hold schools responsible for economic and social improvement. The research findings do not translate into a recipe for the creation of a more effective school (Sammons et al., 1995). For example, several large-scale evaluations of school improvement projects based upon the correlates of presumably effective schools have not led to any significant and sustainable improvements in school outcomes (Wyatt, 1996). There is no simple combination of factors (e.g., high expectations, positive reinforcement, and a measure of home–school partnership) that, when combined, produce a more effective school.

The criticisms of SER come from three distinct perspectives: the political–ideological focus of the research, its theoretical limitations, and its methodological flaws (Luyten et al., 2005). The first, political–ideological concerns, arises from the observed close ties between SER researchers and policy makers (Goldstein & Woodhouse, 2000; Luyten et al., 2005). Criticisms center on the incorporation of SER into government policy, as cognitive test results are chiefly used to address research questions while little attention is paid to other factors that affect student achievement (i.e., housing, health, and employment) (Thrupp, 2001). This appears more in line with governmental agenda than research and does not come close to addressing those larger

goals common to national education systems (e.g., social development) (Luyten et al., 2005). There is some concern that many aspects of schooling cannot be measured with tests, yet tests are the major source of data for such SER school comparisons (Bracey, 2000).

A second criticism suggests that SER studies are based upon simple linear relationships of school input, context, and process (Luyten et al., 2005), and as a consequence, only those variables most malleable and measurable receive attention (Scheerens & Bosker, 1997). Thrupp (2001) complains that the focus on malleability ignores important and informative areas such as background characteristics, student composition, and curricula. For example, Aptitude-Treatment Interaction (ATI) methodology takes individual differences into account to assess the degree to which treatments have differing effects as a function of personal characteristics (Snow, 1991). Finally, from a methodological perspective, SER is criticized for its over-reliance on quantitative achievement data, its cross-sectional approach, and its focus on successful schools (Luyten et al., 2005). Factors that enhance effectiveness can be quite different from those that lead to ineffectiveness. School effectiveness researchers remain focused on observable events and outcomes—those that can be measured statistically—instead of social processes, which do not lend themselves as easily to quantification (Willmott, 1999).

Suggestions for improvement. Suggestions in the literature to address these limitations include more longitudinal research with an eye to the process of how ineffective schools improve and effective schools decline (Scheerens & Bosker, 1997) and the use of statistical techniques to capture the multilevel nature of educational data (Creemers, 2006). Additionally, it has been suggested that large-scale data sets, both national and international, be developed to study the differences in schools and classrooms through data collection of more than just simple standardized achievement measures (e.g., adding additional factors such as demographics of the

student and school environment within the larger social fabric) (Creemers, 2006; Luyten et al., 2005). PISA is one such study that provides an important and interesting data source for secondary analysis from an educational effectiveness perspective (Creemers, 2006).

Scientific Literacy and Conceptual Change

Scientific Literacy

Science education has emerged as a central goal for many national education systems around the world (McEneaney, 2003) and is identified as necessary for the economic growth of a nation as well as the maintenance of a functioning democracy (Keeves, 1995). Current thinking about the desired outcomes of science education for all citizens includes the development of a general understanding of important scientific concepts and exploratory frameworks, an appreciation for the methods that science uses to derive evidence to support its claims, and a concept of the strengths and limitations of science in the real world (Turmo, 2004). Partially because of the economic importance and societal need for a scientifically literate population, the OECD developed PISA to measure scientific literacy as one of its three main outcomes.

Science literacy was the major focus of the PISA 2006 assessment. PISA measured scientific literacy across a continuum of students' demonstrated knowledge of scientific facts and principles as well as their ability to apply these to contextual problems (OECD, 2006). Individual student scores were reported in three competencies (identifying scientific issues, explaining phenomena scientifically, and using scientific evidence) and for overall science performance. Additionally, and new for 2006, the main assessment also included questions on attitudes toward science alongside the questions for cognitive abilities and knowledge. It was believed that an understanding of science and technology central to a student's preparation for life in modern society would help students participate and actively contribute to public discourse as well as aid

them in understanding how science and technology contributes to their daily existence (OECD, 2006).

The term scientific literacy—chosen by PISA because it characterizes the broad, multifaceted nature of the construct being measured—is defined as "the capacity to use scientific knowledge, to identify questions and to draw evidence-based conclusions in order to understand and help make decisions about the natural world and the changes made to it through human activity" (OECD, 2006, p. 25). Scientific literacy is conceptualized in PISA as a continuum from less to more literate, with a less developed individual limited to factual knowledge and a more literate student able to model, predict, and explain scientific constructs.

Although no consensus currently exists on the exact definition of scientific literacy, common to all definitions is that it involves at least some science (both content and process) and is accessible to all students with appropriate pedagogy (McEneaney, 2003). The American Association for the Advancement of Science (AAAS) published a set of recommendations to define scientific literacy that include an understanding of science concepts and their applications to real life; the process of inquiry; the nature of science; and the relationship between science, technology, and society (Lau, 2009).

Criticisms emerging from this definition of scientific literacy include the relative silence on the roles of reading and writing in science education (Yore & Hand, 2003) and the focus on knowledge, learning, and education separate from the traditional view of literacy (i.e., being able to read and write), as discussed by Hand, Alvermann, Gee, Guzzetti, Norris, Phillips, Prain, and Yore (2003). Norris and Phillips (2003) further expand this idea by defining the traditional view of scientific literacy as fundamental and the more recent view as derived. Hand et al. (2003) suggest that science literacy should be reconceptualised to account for this fundamental literacy

definition as well as the more derived one. PISA's definition of scientific literacy does just this by including both the fundamental and derived views, not linking the definition to a national curriculum, and referencing it to long-term learning (Yore, Pimm, & Tuan, 2007).

The lack of agreement on the definition of scientific literacy does not appear to hinder attempts to measure it at local, national, and international levels. Keeves (1995) (see also Hodson, 2006; Laugksch, 1999; Simpson & Anderson, 1992) has commented that the reasons for the increased attention directed toward scientific literacy are multifaceted. First, because economic growth has been linked to favourable test scores at the international level (Hanushek et al., 2008), it is important for all nations to sustain technological and scientific development related to economic wealth. Second, a focus on scientific literacy is necessary so that members of the general public can cope with technological advances in society and the workplace. Third, citizens in modern democracies need to understand and make decisions concerning the many complicated issues related to scientific and technological advances (Simpson & Anderson, 1992).

Social Constructivism and Conceptual Change

Social constructivism—the belief that understanding and learning require an active process of interpretation within a social and cultural setting by the learner—has garnered increasing attention in science education (Duit & Treagust, 2003). In contrast to a more traditional view of learning and instruction (i.e., thinking resides in the mind, learning and thinking are uniform across individuals, and formal instruction transmitted from one person to another leads to knowledge and skill development), social constructivism suggests that knowledge is constructed by individuals as a result of situational experience (Schunk, 2000). Social constructivists view learning as a social process. Learning does not take place only within an individual, nor is it a passive development of behaviours that are shaped by external forces

(McMahon, 1997). Meaningful learning occurs when individuals are engaged in social activities.

Fundamental to social constructivism is the idea that learning about science and doing science are more important than learning scientific knowledge (Hodson, 2006). Constructivist teachers do not instruct in the traditional sense of content delivery but establish classrooms in which learners become actively involved through manipulation of materials and social interaction (Schunk, 2000). PISA 2006 has sought to reflect this idea of social constructivism by measuring students' abilities to understand and apply science in their assessment instead of simply assessing science content as reflected in more traditional school curriculum.

A foundational idea in this active learning process is that of conceptual change. In the classic model of conceptual change, students are confronted with an experience that challenges their previous understanding and initiates a dramatic or revolutionary transition in understanding (Duit, 2003). From a constructivism perspective, teaching to encourage cognitive conflict involves presenting students with experiences that provide disagreement and then directing instruction to help resolve these. According to Tyson, Venvile, Harrison , and Treaurst (1996), if the learner is dissatisfied with his or her previous conception, and if an available replacement concept is intelligible, plausible, and fruitful, accommodation of the new concept will follow. However, there appears to be no study to date that can uncover the complete removal and replacement of a student's prior concept. As a result of such findings, there is a growing line of criticism against conceptual change models that focus on cognition and neglect the social issues of knowledge construction (Duit & Treagust, 2003).

Although these initial conceptual change approaches contributed to improved research and understanding, they failed to translate into something normal teachers could use in their classrooms (Duit & Treagust, 2003). However, there is convincing evidence that cognitive and

affective issues are closely linked (Duit, 2003). Conceptual change strategies must be embedded in what is called “conceptual change supporting conditions”, which include such factors as student interest, motivation, self-concept, and the class and school environment (Duit &Treagust, 2003). As a direct response to the limitations of this “cold” conceptual change model (i.e., one that fails to address attitudinal backgrounds in students), Tyson et al. (1996) proposed a multi-dimensional interpretive framework for conceptual change. This conceptual change model accounts for the pre-instructional conceptions of the student, the science content, and the path between them as students construct their own knowlede.

Because learning in science is influenced by the way students feel toward science (Simpson, 1991), if students acquire positive attitudes—along with knowledge and skills—during school years, it is easier for them to acquire additional scientific knowledge in later life (Hodson, 2006). If students receive less than adequate exposure to science in the elementary schools, or if they experience frustration in their first formal science classes in middle school, they are likely to turn away from science and become citizens who are less scientifically literate and/or uninterested in science (Simpson & Troost, 1982). These affect variables identified as having influence on science learning and viewed necessary to facilitate “conceptual change supporting conditions”, are identified and measured by PISA (i.e., self-concept of learning science and self-efficacy toward learning science). Details on these affect variables in PISA and how they may be used to help identify indicators that contribute to scientific literacy on an international scale are provided in the following section.

Student Climate Variables

Understanding relationships that promote educational attainment is one of the main issues in educational research. Studies involving personal beliefs suggest that students with positive

views of themselves strive to succeed and overcome obstacles (Bong & Clark, 1999). Students become agents of their own learning within classrooms and are no longer simply recipients of information (Bandura, 2006). This active involvement on the part of the student is linked to the constructivist ideas mentioned previously. For example, Tuan, Chin, and Shieh (2005) uncovered that when students perceive that they are capable, think the science tasks are worthwhile, and are motivated to gain competence, they will be willing to make the sustained effort needed to achieve conceptual change, scientific understanding, and increased achievement.

The beliefs children create, develop, and hold to be true about themselves are assumed to be of vital importance to their success and failure in a variety of domains, with school being of particular interest. Children with different self-beliefs demonstrate different levels of cognition and social and emotional engagement in school (Bong & Shaalvik, 2003). The assumption that children's self-beliefs are tied to their thinking and functioning is reflected in current academic motivation research focused primarily on the self (Pajares & Schunk, 2002). For students to learn autonomously, they must critically assess their own skill sets as well as the difficulty of the task presented to them. Two ways of defining these beliefs are to identify how much students believe in their own ability to handle tasks effectively and to overcome challenges (i.e., self-efficacy) and students' general beliefs in their own academic abilities (i.e., self-concept) (OECD, 2006).

Self-concept and self-efficacy are possibly the two most well researched constructs related to academic motivation to date, and this research has contributed greatly to an understanding of how critical students' views can be in their academic success (Bong & Clark, 1999). Pajares and Schunk (2002) suggest that self-concept beliefs are formed by asking questions of being and feeling (i.e., "Am I any good at science?"), whereas self-efficacy beliefs are formed by asking "can" questions (i.e., "Can I do this science question?"). PISA 2006

measures both of these constructs in relation to science achievement through the student questionnaire.

Self-efficacy

Attempts to measure or explain phenomena such as academic achievement without discussing the role played by self-efficacy are not possible (Pajaras & Urdan, 2006). Self-efficacy deals primarily with cognitively perceived capability of the self (Bong & Clark, 1999) and represents individuals' expectations and convictions of what they can accomplish in given situations (Bong & Shaalvik, 2003). Bandura (1977), through his social cognitive learning theory of human functioning, proposed that how one behaves can be predicted by the beliefs one holds about his or her capabilities and defined self-efficacy as "the conviction that one can successfully execute the behaviour required to produce the outcomes" (p. 79). Self-efficacy affects students' behaviours by influencing them to engage in those tasks toward which they feel confident, encouraging them to stay with and exert more effort at difficult tasks, and influencing emotional reactions by creating feelings of confidence as tasks increase in difficulty (Pajares & Schunk, 2002).

Self-efficacy has a number of distinctive characteristics that allow comparison to other self-belief constructs and provide measurement guidance. Zimmerman and Cleary (2006) suggest four such characteristics. First, self-efficacy judgements focus on perceived capabilities to perform an activity and not on personality or psychological traits. Second, self-efficacy is domain-, as well as context- and task-specific. For example, a student may express lower self-efficacy in a competitive classroom context compared to that expressed in a non-competitive one. Further, within that competitive classroom, a student may have differing levels of self-efficacy for tasks such as addition versus subtraction. Third, self-efficacy is based upon mastery

performance criteria and not on normative criteria. For example, students rate how well they can perform a science lab write-up compared to some set level of performance instead of compared to how well their peers can write up the lab. Fourth, self-efficacy beliefs are typically assessed prior to engaging in a task.

Adolescence is an opportune time to measure the construct of self-efficacy as students are required to navigate a more challenging academic environment. If they do so unsuccessfully, academic outcomes will decline, potentially leading to a loss in self-efficacy about succeeding in school (Zimmerman & Cleary, 2006). PISA 2003 showed a significantly positive association between students' self-efficacy in mathematics and their mathematics achievement (OECD, 2005).

PISA is in line with suggestions on how best to capture self-efficacy in written questionnaires—namely to emphasize the self-judged confidence of students regarding successful execution of the required behaviour under specific situations, to not reference emotional reactions that may arise out of the self-appraisal, and to focus on perceived capabilities to meet criteria for success (Bong, 2006). Bong and Shaalvik (2003) suggest a method for measuring academic self-efficacy that involves presenting problems to students that are similar to the ones they will be asked to solve in the later assessment or classroom situation. Students then estimate their confidence in solving each correctly. PISA 2006 followed this method for measuring the domain of science self-efficacy. Generally in PISA 2006, students who reported higher levels of self-efficacy in science also demonstrated higher performance (OECD, 2007).

Self-concept

Although the definitions of self-concept vary widely (Bong & Clark, 1999), there is some

consensus that in essence, it is composed of what an individual believes about himself or herself and is made up primarily of the beliefs one holds to be true about one's experience (Pajares & Schunk, 2002). Marsh and Craven (1997) refer to self-concept as those self-perceptions formed through interactions with the environment and through environmental reinforcements and reflected appraisals from others. Self-concept refers to a generalized self-assessment made up of beliefs such as feeling of self-worth and competence (Zimmerman & Cleary, 2006). Self-concept is composed of two components: a cognitive component, which consists of awareness and understanding of the self and its attributes, and an affective component involving one's feelings of self-worth, which references approval or disapproval of the self in any given situation (Bong & Clark, 1999).

Although self-concept and self-efficacy may appear similar, they represent different constructs. Self-concept measures the general level of beliefs that students have in their academic abilities and is composed of cognitive and affective facets. The cognitive facet consists of awareness and understanding of the self and its attributes, and the affective facet involves one's feelings of self-worth and refers to approvals or disapproval of the self in any situation (Bong & Clark, 1999). Self-concept was also measured in PISA 2006, as it is both an important outcome of education as well as a trait that correlates strongly with student success (OECD, 2006). Unlike self-efficacy, there was not the same uniform association between students with strong self-concept in science and higher performance. This difference is potentially explained by the idea that students' self-concepts are at least partially influenced by their peer group and supported by the level of variation observed within countries, schools, and classes.

Student Context Variables

The student level context variables used in this study are detailed as follows.

Socio-economic Status

SES is topical to the study of educational outcomes as it is believed that families with higher SES enable their children to access support, materials, and opportunities that put them ahead of their peers who do not have similar access (Bradley & Corwyn, 2002). Research on human development has repeatedly and consistently identified a relationship between people's health and well-being and socio-economic factors such as income, occupational prestige, and level of education (Willms, 2002). Children who grow up in poverty are more vulnerable, are more likely to experience poor health, have learning and behavioural difficulties, underachieve at school, become pregnant at an early age, have lower skills and aspirations, receive lower wages, and be unemployed or welfare dependant (United Nations Children's Fund [UNICEF], 2007). Student-level SES (traditionally defined as a function of parental income, education level, and occupational status) is positively but weakly correlated with measures of academic achievement (White, 1982). Differences across race, ethnic, and immigrant groups help to explain much, but not all, of the variations in educational outcome (Kao & Thompson, 2003). However, just how socio-economic background influences educational inequality is not well understood (Marks, Cresswell, & Ainley, 2006).

Operationalization. Despite its familiarity, the term SES has not achieved widespread consensus in its definition. There are currently two camps, one arguing to define it as a class or economic position and another believing it should be based upon social status or prestige (Bradley & Corwyn, 2002). Although these two appear similar, they can be divided into capital in the form of material resources versus more nonmaterial resources such as those acquired

through education and social connections. Coleman's (1988) idea of capital in the form of resources and assets appears to be the foundation for the PISA definition of SES as a combination of financial capital (e.g., material resources), human capital (non-material resources), and social capital (e.g., social connections) and is likened to human health and well-being. PISA distinguishes three components of SES based upon the extent to which material, cultural, and social variables are emphasized through its index of economic, social, and cultural status (ESCS). PISA further hypothesizes that this multidimensional measure of SES will have a stronger association with academic achievement than a measure with fewer component variables.

In education, the concept of material resources (i.e., economic capital) focuses on the idea that poor families have less access to educational resources than children coming from higher SES families, as differing access is believed to result in differing student performance. Wealthy families are able to buy educational success by sending their children to schools with higher mean SES, moving to better neighbourhoods, and providing out-of-school support (Marks et al., 2006). Those children from high SES homes are exposed to an intellectual climate that encourages aspirations and motivations to achieve, and academic performance follows. In this way, the school effect on academic achievement is mediated by this home variable of SES. However, this mediation may not hold for all nations, as material resources in less developed nations may be a more important component of socio-economic inequality in education (Marks et al., 2006), and this hypothesis remains to be tested across a wide range of countries (Nonoama-Turumi, 2008).

Cultural capital, based upon the work of French sociologist Pierre Bourdieu, details how in many countries, direct links exist between parents' cultural background and student performance (Turmo, 2004). Children from high-status backgrounds are at an advantage as they

better understand the hidden curriculum that underlies the educational system and are more favourably judged by its gatekeepers (i.e., teachers and administrators). This understanding is felt to be more important in the humanities than in sciences and mathematics (Marks et al., 2006). Again, this linkage also remains to be tested across a number of countries with wide-ranging national income levels (Nonoama-Turumi, 2008). The central idea behind social capital is that social relationships and the personal networks that come from them are a resource that translates into valued outcomes (Croll, 2004). The traditional hypothesis about social capital is that students do better at school if they have a close social network surrounding them where parents, children, and teachers collaborate and know each other intimately (Turmo, 2004).

SES and academic achievement. White (1982) carried out a meta-analysis of studies published prior to 1980 that examined the relationship between SES and academic achievement. The meta-analysis consisted of 101 studies yielding 636 correlation coefficients estimating the typical strength of these reported coefficients (White, 1982). He revealed that when measured at the student level with a traditional definition (i.e., income, occupation, and education level), only a weak relationship to academic achievement was found accounting for less than 5% of the variance at the student level (r = .22). However, White found that the relationship was strong if measured at the school level (r = .73), and the other measures of SES—such as home atmosphere—were stronger predictors than the traditional three of income, occupation, and education level (White, 1982).

In a replication of White's original study, Sirin (2005) meta-analyzed SES-achievement research focused on data from 1990 to 2000. Like White (1982), Sirin also identified the concern around misinterpreting individual-level inferences made on the basis of group-aggregated data (i.e., an atomistic fallacy) and took steps to attenuate that concern. Seventy-five independent

samples were collected, of which 207 correlations were coded, with an overall mean of .29 and median of .24 (.28 for student-level data and .60 for aggregated school-level data) (Sirin, 2005). According to his analysis, parental position in the socio-economic structure of society has a strong impact on student academic achievement, and this relationship is further moderated by factors such as type of SES measured, student characteristics, grade, and minority status (Sirin, 2005).

Although, as mentioned above, lower SES and depressed academic outcomes are correlated, the strength of this relationship is surprisingly varied (Sirin, 2005). Similarly, immigrant status can also be correlated to lower SES as well as linked to lower academic outcomes. However, the literature is not definitive in this relationship.

Immigrant Status

In addition to attitude and parental socio-economic influences on academic achievement, there remains variation in academic outcome due to racial and ethnic factors. Understanding race, ethnic, and immigration variations in educational achievement and attainment is more important than ever as the population in the developed world becomes more diverse (Clarkson, 2008; Kao & Thompson, 2003). Immigrants represent a crucial component of the future for developed societies, and having a better understanding of parents' and children's experiences and the paths taken toward becoming members of society may facilitate this process. The children of immigrants will define the direction and outlook of their respective ethnic communities (Portes & MacLeod, 1996). However, the performance of immigrants is a topic rarely discussed in the literature (Entorf & Minoiu, 2004). One of the reasons for the creation of the PISA measure is to provide a rich source of information for educational policy makers in those countries that participated in the survey (OECD, 2006). PISA collects information on immigrant status through

the student questionnaire.

Immigration trends. In recent decades, the wealthier, more-developed countries of the world have been increasing in population due to positive net migration (UN, 2006). North America, Europe, and Oceania are the major areas that are currently experiencing the highest gains due to net immigrations, whereas Africa, Asia, and Latin America are losing population due to net migration (UN, 2006). However, these general patterns mask substantial variation.

North America has been adding approximately 1.3 million people annually since 1990 with the United States of America accounting for more than 80 percent of this net migration (UN, 2006). In 2001, Canada, the other North American nation that receives net migration, passed the Immigration and Refugee Protection Act, shifting from its previous occupation-based model for granting admission to one emphasizing education, language, and transferable skills (Ray, 2002). At the time of the 1996 census, almost 5 million foreign-born individuals lived in Canada, accounting for almost 18% of the population (Ray, 2002).

Oceania added 86,000 persons annually thru net migration over the 1990–2000 period (UN, 2006). Currently, nearly a quarter of Australia's population was born in another country (Inglis, 2004). The opening of Australia's immigration policies in 1970 shifted away from a preference for European immigrants. Three criteria—family migration/relatives, skills, and humanitarian need—are currently identified as the basis for selection (Inglis, 2004). New Zealand is a similar case. Just slightly fewer than 20% of New Zealand residents recorded a birthplace other than New Zealand (Bedford, 2003). Like Australia and Canada, New Zealand's immigration policy is currently based on a point system that favours immigrants who can provide economic and social benefits to New Zealand.

Western Europe has of late become an area of positive net migration and in 1990–2000

added 1.1 million persons annually to its population through immigration (UN, 2006). In the last third of the 20th century, Spain evolved from its traditional role as a sending country and a transit country for migrants headed north to a destination country for immigrants (Pérez, 2003). The number of foreign residents in Spain increased an average of 7% annually from 1980 to 1991. As of 1992, this figure had climbed to 10% annually. While in need of immigrants to bolster economic development and maintain a dynamic workforce, Germany is struggling with a population that is unsupportive toward immigration, seeing it as a threat to high wages, the welfare state, and cultural homogeneity (Munz, 2004). In 2001, the government counted an estimated 1.1 million refugees in the legal foreign population of 7.3 million, which comprised 8.9% of the total population of Germany.

Immigrant performance orientation. Three differing opinions are held regarding the discussion of ethnic groups and their differing educational achievement. The first deals with cultural groups' differing attitudes toward schooling. Ethnic groups have cultural orientations that can either help or hurt their odds of economic (or educational) advancement relative to other groups (Kao & Thompson, 2003). For example, immigrants—compared to their non-immigrant peers—have reported higher motivations toward learning, positive attitudes toward school, and a strong belief in their own abilities (Schleicher, 2008). However, the often stereotypical way that immigrant students are portrayed, for example the Asian American model minority, is overly simplistic. This stereotyping can be damaging as it potentially blames underachievement on an ethnic group and conceals the variance within ethnic groups behind a pan-ethnic shield (Ngo, 2008). The differing patterns of immigrant achievement suggest that an understanding of this phenomenon has yet to be fully explored and identified.

The second opinion deals with how the structural position of ethnic groups affects their

environment. Because parental social class has a considerable impact upon a child's eventual educational achievement, socio-economic status is credited with these differences in outcome for children (Kao & Thompson, 2003). The third opinion postulates on the difference in innate intelligence between ethnic groups; however, the reasoning behind this theory is specious, and it will not be addressed to any degree in this work. Put simply, "no gene has been identified as affecting test scores" (Kao & Thompson, 2003, p. 420).

Immigrant academic achievement. Levels of adaptation among young immigrants are usually measured by educational attainment (Zhou, 1997). For example, it is reported that many immigrant children in America tend to do better than their American-born peers with similar SES backgrounds attending neighbourhood public schools (Zhou, 1997). Some academic achievement research among immigrant youth indicates that immigrant students—especially among the first or second generation—are more successful than their non-immigrant peers (Clarkson, 2008). However, this academic achievement varies significantly by race and ethnicity and generally, in most industrialized countries, immigrant students do not do as well as native students (Ammermueler, 2007; Entorf & Minoiu, 2004; Huang, 2000; Marks, 2005).

In an exploration of immigrant youth educational choices in the United States as they transitioned to college and adulthood, Tseng (2006) uncovered that children of immigrants were not only more successful on achievement measures, but that they chose courses of study with higher mathematics and science content than their U.S.-born peers. Tseng theorized that because immigrant students' parents were limited by cultural and language barriers in their new homes, they directed these aspirations for greater social and economic mobility to their children and that this is a predominant factor in the contemporary immigrant experience (Tseng, 2006). However, the idea of a singular, shared pathway conceals the existence of competing and different

immigrant experiences with their new cultures (Ngo, 2008).

On the other hand, there is a research stream (e.g., Tseng, 2006) that explores the variety of explanations for why immigrant students generally perform at lower levels on national and international assessments than their native peers. Some of these explanations include socio-economic factors, socio-cultural factors, and the types of schools immigrants find themselves attending (Marks, 2005). Socio-economic factors such as lower work status of parents or lower income have been linked to lower educational outcomes of children (Portes &MacLeod, 1996). Socio-cultural factors emphasize the differences between the immigrant and host communities (Kao & Thompson, 2003; Leung, 2002). Schools also influence outcome, because immigrants tend to find themselves in schools with high proportions of other immigrants (Zhou, 1997).

When Marks (2005) looked at the contribution that socio-economic, socio-cultural, and school factors had on the relative performance of first- and second-generation immigrants from 20 countries using the PISA 2000 data, he uncovered that although all three explain most of the difference between immigrant and non-immigrant performance, socio-economic factors were by far the most important reason for the weaker performance of immigrant students. Entorf and Minoiu (2004) also used PISA 2000 to econometrically evaluate the importance of social class, migration background, and language spoken in the home for European countries (France, Finland, Germany and the UK) compared to countries of traditional immigration (i.e., Canada, Australia, and New Zealand). They discovered that the impact of being an immigrant student who spoke a foreign language at home was sizable. These effects were greater in Europe (i.e., Germany 105.7 points lower) than in traditional nations of immigration (i.e., Canada 25.5 points lower) for the PISA reading literacy score.

In a series of case studies, Li (2008) and Xu, Connelly, He, and Philion (2007) studied

immigrant Chinese families' experiences in Canada. Li used Coleman's ideas of capital (i.e., economic, cultural, and social) to study four families and how home variables influenced second-language learning. She uncovered three things:

1. The three forms of capital were difficult to differentiate and overlapped greatly.
2. Simply having economic capital is not enough to ensure successful language acquisition; rather, what a family did with the capital was more important.
3. Families that oriented children to academics and socialized children within the larger community were more successful with acquiring second-language literacy (Li, 2008).

Xu et al. (2007) looked at a Chinese immigrant family in Canada through narrative inquiry and the challenges its members were having adjusting Chinese values to Canada. The authors commented on how the notion of Asian immigrants being a "model minority" was potentially damaging as it created a hidden minority of students. Resource allocation and prevailing attitudes conspire against students from these model minorities who are not as successful as is expected. Not only do they miss out on needed academic support, but they can also be viewed as a poor representative of their culture who does not take advantage of inherent talents.

A number of studies have attempted to identify and account for the differences in academic achievement of non-European immigrants into the United States (see Blair & Qian, 1998; Fuligni, 1997; Portes & MacLeod, 1996). Fuligni (1997) looked at the family background of Latino, East Asian, Filipino, and European immigrants within Southern California to determine the relative contribution it might make to educational achievement. Interestingly, foreign-born students did better in mathematics and English than third-generation immigrant peers. These same foreign-born students demonstrated a stronger emphasis on the value of education, and differences in attitudes and behaviour existed across ethnic groups (Fuligni,

1997). The motivation and effort expended by these first-generation students enabled them to overcome the limitations of a new language and culture to be successful in the education system. This supports the idea that immigrant children tend to do better than their American-born peers of similar SES background attending schools in the same neighbourhood (Zhou, 1997).

Blair and Qian (1998) studied differing educational performance among the Asian American population by looking at the 1992 National Educational Longitudinal Study (NELS), a nationwide representative sample of high school students' academic achievement and demographic information. The study identified differences in socio-economic status and household income across five groups: Chinese, Filipino, Korean, Southeast Asian, and Japanese students. They concluded that family socio-economic factors do appear to have an effect on Asian students' educational performance, but they also found that tremendous variability across the groups in terms of predictive strength of these characteristics persists.

Similarly, Portes and MacLeod (1996) sampled 5,266 eighth- and ninth-grade students in California and Florida who were second-generation immigrants of Cuban, Vietnamese, Mexican, and Haitian descent. Not surprisingly, both the family SES and mean socio-economic school level played significant independent roles. What was surprising was that national background also played a significant and independent role when the other two were controlled. SES is not all that counts, as immigrant students from intact families show better academic achievement and stronger educational aspirations than immigrant students from single-parent families (Zhou, 1997).

As commented, schools influence outcome because immigrants tend to find themselves in schools with high proportions of other immigrants (Zhou, 1997). Historically, segregation has contributed to inequality among racial and ethnic groups (Rumberger & Willms, 1992). Data

from the National Center for Educational Statistics in the United States show that half of Asians and almost half of Whites are on the highest academic track in American schools, while Blacks, Hispanics, and Native Americans are more likely to be in the general and lowest track (Kao & Thompson, 2003). Unfortunately, decisions to segregate or track students are related to marks, and this segregation begins quite early. Early marks correlate strongly with later ones, and early marks for Black students have been shown to be more predictive than for White students; however, little is actually known about how young children's marks are determined (Entwisle & Alexander, 1988).

Educational systems that reward ability and effort rather than SES (i.e., ensuring that objective criteria are used to allocate students between locations in the school system) have the potential to reduce the intergenerational social advantage/disadvantage cycle. However, other systems may increase social inequality through approaches that assist those with a higher SES background and place barriers in the path of those from lower ones (Marks et al., 2006). School types, academic or vocational, are often associated with particular education and occupational pathways, and in many countries, particularly in Europe, school systems are tracked—that is, students are assigned to different school types on the basis of prior performance (Marks et al., 2006).

Educational researchers argue that a system of early differentiation by skill level (e.g., Germany) has a negative impact on academic achievement for students who come from lower social backgrounds—many of whom are immigrants (Entorf & Minoiu, 2004). According to Kirsch, Jong, Lafontaine, McQueen, Mendelovits, and Monseur (2002), between-school differences in the academic achievement of students tend to be largest in European counties that track students formally (e.g., Germany) and only moderate in those that do not (e.g., Australia,

Canada, and New Zealand). This difference stems from the fact that European countries admit socially less advantaged immigrants with labour-related backgrounds (Entorf & Minoiu, 2004). The so-called countries of traditional migration follow policies that admit immigrants with high education, good language skills, and flexibility who more quickly and efficiently match their skills with opportunities in these countries (Entorf & Minoiu, 2004).

Examining Achievement Across Cultures

Research on school effectiveness has shown heavy ethnocentric tendencies (i.e. focused on single Western education systems) with no clear educational effectiveness studies across countries (Kyriakides, 2006). Attempts to respond to these weaknesses through an examination of similarities and differences in the relationship of student and school climate and context variables to academic outcomes through data from large-scale, standardized international assessments have been suggested in the literature (Crossley & Watson, 2003; Creemers, 2006). These assessments, such as TIMSS (Leung, 2002) and PISA (OECD, 2006), collect demographic and individual differences data from students (such as attitudes and beliefs about schooling) and academic achievement data from students in several countries.

The student background items answered by 15-year-old students in the PISA 2006 assessment allow for the examination of the relationship between some common student self-beliefs in science and academic achievement. This allows for exploration of both the patterns of relationships between these science self-beliefs and science achievement, and how these items relate to achievement in other domains (mathematics and reading literacy). Additionally, the data available in the PISA 2006 data set allows some preliminary investigation of similarities and differences in patterns of relationships between these same self-belief variables as well as the constructs of socio-economic status, immigrant status, and academic achievement, and how those

variables are related to school environment in several western countries that are popular destinations for international migration.

Research Problems and Objectives

Utilizing data made available from the PISA 2006 comprehensive reports, this dissertation comprises two major areas of focus. Initially, this study will explore possible links between academic success and both climatic variables, including science self-beliefs, and contextual variables, including social and cultural background. In our multicultural, mobile world, understanding these context and climactic variables will enhance school effectiveness research theory and build our conceptual understanding of academic achievement. Second, the conceptual assumption made by early SER studies that school populations were homogenous (Teddlie et al., 2000) will be explored. Thrupp (2001) argues that student background characteristics and student composition in schools are often overlooked by SER in the search for explanatory variables. The increase in immigration in the latter part of the 20th century may make this assumption invalid. The consideration of heterogeneity at the student level is often missing from this theoretical perspective as well as research findings in this area. By looking at science self-beliefs at the student level and cultural and social differences at the student and school level for science achievement across a variety of nations of high immigration (i.e., Spain and Germany, Canada and the United States, and Australia and New Zealand), this research will question the relevance of the assumptions of homogeneity in SER. As the methods employed here are exploratory, the potential associations are stated in the form of research questions, rather than hypotheses:

1. What are the relationships among science self-concept, science self-efficacy, and science achievement for students in the participating nations of PISA 2006?

2. How much of the variance do cultural, social, and economic capital (the elements of the SES variable in PISA) for each country in PISA 2006 account for when predicting scientific literacy?
3. What is the empirical relationship between scientific literacy and science self-concept, science self-efficacy, SES, and immigrant status as defined by PISA for students in Spain, Germany, Canada, the United States, Australia, and New Zealand?
4. What is the relationship between scientific literacy and science self-concept, science self-efficacy, SES, and immigrant status achievement in reading and mathematics literacy for the countries listed above? Do we see the same patterns as with science achievement? How do the relationships compare across achievement domains?
5. What is the relationship of school-level indices (school SES and proportion of immigrant students) to the student-level variables of science self-efficacy, science self-concept, SES, and immigrant status in the same countries as above across all literacy domains?

Chapter 3: Research Methodology and Methods

Secondary Data Analysis

Overview

The use of existing data sets is quickly becoming an important part of behavioural science research. Significantly large samples are used to address specific, large-scale questions (Bell-Ellison & Kromrey, 2007; Friedman, 2007). In these times of declining resources for research in the social sciences and as independent data collection becomes more challenging (Kiecolt & Nathan, 1985), one of the key advantages of secondary analysis is that it offers all researchers opportunities for empirical research that had previously been the privilege of the few (Hakim, 1982).

Secondary analysis has a long history in social research (Cherlin, 1991) largely because central governments have had long-standing and active roles in collecting social data. Population census data collection began in 1801 in Britain and in the 1790s in the United States (Hakim, 1982). Its rich and varied intellectual tradition is evident from the work of Emil Dukheim on suicide rates using official statistics in France (1897), Karl Marx's use of unofficial economic statistics from Britain to document "class struggles" (1848) (Frankfort-Nachmias & Nachmias, 1996), and subsequent analysis of the work of Lewis Terman and his long-term studies of gifted children, which originated in the 1920s (Hakim, 1982). However, a revolution in secondary analysis occurred in the 1970s when governments transitioned from primarily administrative census data collection towards an emphasis on data from sample surveys (Hakim, 1982). This change allowed for more detailed questions to be asked and analysis to be conducted for these multiple purposes.

Advantages and Limitations of Secondary Data Analysis

Secondary data analysis offers promise for furthering our understanding of human behaviour. According to Rogers, Anderson, Klinger, and Dawber (2006), the Council of Ministers of Education in Canada, recognizing these potential benefits, has requested secondary data analysis of achievement and survey data linking contextual and educational factors to student performance. Provincial ministries of education, by making collected data available to researchers, allow for deeper and more comprehensive analyses that relate variables at the student, class, and school level to achievement measures. This type of research allows a more large-scale examination of the relationships between variables affecting the classroom and students and is potentially useful to school and ministry officials.

As with any research strategy, secondary data analysis has both advantages and

limitations. There are three basic reasons for the increasing use—by social scientists—of data collected by other investigators for research purposes other than for the original reasons for collection: conceptual–substantive, methodological, and economic (Frankfort-Nachmias & Nachmias, 1996). Although the advantages of secondary analysis clearly outweigh the disadvantages (Kiecolt & Nathan, 1985), there are also drawbacks. The limitations include the availability of the data, the level of observation, the quality of the data, the time involved in understanding the data set, and the possibility that the data might be outdated. Each of these will be discussed in some detail, with relevant examples, over the following few sections of this paper.

Advantages. The conceptual–substantive position addresses how best to answer the research question, as secondary data may be the only data available to answer specific questions on historical context (Frankfort-Nachmias & Nachmias, 1996) or provide comparative change over time (Brooks-Gunn, Elder, & Phelps, 1991). In the case of the PISA data, comparisons within and between nations may enlarge the scope of generalization and provide additional insights. This advantage of secondary data analysis is well detailed by the National Institute of Health (NIH) in the United States. The NIH (2003) states that:

> Sharing data reinforces open scientific inquiry, encourages diversity of analysis and opinion, promotes new research, makes possible the testing of new or alternative hypotheses and methods of analysis, supports studies on data collection methods and measurement, facilitates the education of new researchers, enables the exploration of topics not envisioned by the initial investigators, and permits the creation of new datasets when data from multiple sources are combined (Goals of Data Sharing section, para. 2).

From a methodological standpoint, secondary analysis can provide an opportunity for

replication, longitudinal design, expansion of independent variables, increased sample size and—through triangulation—increased validity of findings (Frankfort-Nachmias & Nachmias, 1996). Secondary data analysis has the benefit of large sample sizes, which aids in greater precision of population parameters and maximized representation through high response rates (Kiecolt & Nathan, 1985). Also, the potential to lend itself to monitoring change over extended periods of time (sometimes longer than the lifespan of the researchers involved) both informs and complements primary data collection by aiding in the direction of data collection and avoidance of costly re-sampling. Survey data may also be used to uncover interesting relationships that can be further explored in smaller observational studies that again may be tested for general applicability using subsequent large-scale surveys (Cherlin, 1991).

Another methodological advantage is that secondary analysis avoids many data collection problems (i.e., appropriate respondents unavailable or declined to participate in the study) (Kiecolt & Nathan, 1985). Specifically, the quality of the data available of these large-scale measures is often exceptional. Again, to reference TIMSS and PISA, the quality of the initial and ongoing investment into creating, validating, administering, and interpreting is psychometrically sound (McQueen & Mendelovits, 2003; Turner & Adams, 2007). These are collaborative projects developed in consultation with representatives of participating groups—countries in the PISA case—in efforts to apply international test guidelines to practice. The PISA data set is developed and based on current primary research, evaluated by experts in the respective fields, pilot tested with groups in various countries, and then field-tested before the final test booklets and questionnaires are created (OECD, 2005). The sample size in these studies is large enough to enable the researcher to draw meaningful conclusions from a wide spectrum of approaches, including descriptive, exploratory, and correlation studies (Castle, 2003). The size of the samples

also provides increased power and generalizability due to the representative sample designs and the large number of useful variables (Bell-Ellison & Kromrey, 2007).

Finally, the economic rationale is obvious because secondary analysis is less expensive than collecting data independently (Kiecolt & Nathan, 1985). There is a lower cost associated with working with these data sets (Hofferth, 2005; Kiecolt & Nathan, 1985), and obtaining secondary data is often easier than obtaining that of typical primary data (Bell-Ellison & Kromrey, 2007). The variety and increasing number of international education achievement measures (i.e., TIMSS and PISA)—and therefore the potential for the application of secondary data analysis in an atmosphere of trying to do more with less money—are enticing. Essentially, the data analysis can be carried out quickly as compared to the alternative of more formal design, collection, and analysis. This is encouraging for researchers at institutions with fewer and/or limited resources to conduct studies (Friedman, 2007). The opportunity for researchers to gain experience by analyzing existing data—thus allowing time for skill and experience to be gained before proposing new data collection—is also noteworthy as an advantage (Castle, 2003; Hofferth, 2005).

Limitations. Predictably, with all the positives of secondary data analysis come limitations. Although some investigators on an individual level are both willing and able to make their original data available upon request, most original data is inaccessible after publication (Church, 2001). Possibly the largest drawback with this approach is that analysis of complex surveys that were collected for purposes other than that of the secondary analysis is problematic (Bell-Ellison & Kromrey, 2007; Friedman, 2007). There is a potential mismatch as the variables accessible to the secondary researchers are unlikely to be exactly suited for the new investigation and are unlikely to be the variables that would have been selected had the secondary researchers

collected the data themselves. An example of this exists in the PISA data as an aggregated ESCS (economic, social, and cultural status) variable for socio-economic status that was selected by PISA, yet the literature would support the inclusion of other additional factors of this predictor (Mueller & Parcel, 1981; UNICEF, 2007).

Additionally, selectivity is necessary when dealing with the sheer volume of these data sets, and the value of both guidance and experience cannot be overstated. For example, the PISA 2006 assessment in science samples more than 400,000 students from 57 countries (OECD, 2007). It is frequently challenging to determine the quality of some of the data in question (e.g., the common concern with validity of self-reporting measures as used in PISA [Schwarz, 1999]). In the case of the ongoing PISA assessment, this data quality question arises with when and where data are collected. As each country only sampled at the student and school level; therefore, no classroom-level analyses are possible. There is a growing body of research on classroom-level practices and international data collection at the classroom level would be a welcome addition to this area (Castle, 2003).

Researchers need to be intimately familiar with data prior to conducting any analysis, and identifying and obtaining appropriate data for the study can consume more time than is originally anticipated (Castle, 2003). Although this may appear to be a general point in research, when working with secondary data, the researchers must often familiarize themselves with the original purpose of the data collection before being able to use the data to answer their own questions. Another disadvantage is the possibility of inhibitions to creativity, as the use of the same data sets repeatedly has the potential to thwart scientific progress (Kiecolt & Nathan, 1985; Friedman, 2007). Although this has the potential to be problematic, it has also proved beneficial as different researchers approaching a topic differently, with differing models and methodologies, provides a

type of convergent validity to findings (Cherlin, 1991).

The final limitation of note with secondary data analysis is that data often dictate the research question (Bell-Ellison & Kromrey, 2007). There is some documented hesitancy of researchers to use secondary data as it does not fit exactly into the deductive positivistic paradigm in social science (Hofferth, 2005).

Although availability of the data, the level of observation and the quality of the data are real limitations to secondary data analysis, these disadvantages may be outweighed by the trade-off of obtaining research answers at a potential low cost in time and in money (Friedman, 2007). Collection of data in national and international assessment projects, such as the General Social Survey (GSS) in Canada or the OECD's PISA, will continue and others will be added to this body of data. As a result, secondary data analysis will likely continue to play an important part in research in education.

The Programme for International Student Assessment

PISA is a project of the OECD designed to provide policy-oriented international indicators of the skills and knowledge of 15-year-old students (Government of Canada, 2008). Three literacy domains are assessed in PISA: reading, mathematics, and science. In each three-year cycle of the assessment, two thirds of the testing time for each participating student is devoted to a major literacy domain: reading in 2000, mathematics in 2003, science in 2006, and reading again in 2009. PISA aims to assess to what degree students approaching the end of their compulsory education have acquired some of the knowledge and skills that are essential for full participation in society (Turner & Adams, 2007) and hopes to answer the following questions:

1. How well are young adults prepared to meet the challenges of the future?
2. Are they able to analyze, reason, and communicate their ideas effectively?

3. Do they have the capacity to continue learning throughout life?
4. Are some kinds of teaching and school organization more effective than others?

General Strengths and Limitations of the PISA Data Set

PISA provides a publicly accessible, large, and significant data base conceived by the OECD in the late 1990s as an "ongoing, periodic international comparative study of the proficiency in Mathematics, Science and Reading of 15 year old students" (Turner & Adams, 2007, p. 238). As previously noted, PISA has been administered in 2000, 2003, 2006, and 2009, with current planning projected to 2015. After each assessment cycle, the OECD makes available the results as well as comprehensive reports detailing literacy outcomes and background variables (i.e., student, family, and school and system factors). These PISA publications may be accessed at the OECD website: http://www.pisa.oecd.org.

The PISA 2006 target population was composed of approximately 20 million students aged 15 years 2 months to 16 years 2 months at the time of assessment and enrolled full time or part time in any educational program in the 57 participating countries. These participating countries combined to represent approximately 90% of the world economy. The sampling was carried out in two stages in order to assign consistent probability of selection to all students in participating countries (Turner & Adams, 2007). At the first stage, schools with eligible students were randomly sampled with probability relative to size. Then 35 students were randomly sampled within each selected school. For schools with fewer than 35 students, all of the students were included. A minimum of 150 schools were sampled in each participating country. This translates to a potential minimum of 5,250 students from each country in the sample with the expectations of 4,500 students to be assessed. The test was typically administered to between 4,500 and 10,000 students in each country. However, some nations (e.g., Canada) in PISA over

sampled to allow for score estimates at a lower level. The sampling criteria required a minimum of an 85% participation rate across schools and 80% within schools, and, in total, the final sample size was more than 400,000 students (OECD, 2007a).

PISA 2006 continued the previous format of paper and pencil tests encompassing 2 hours in two item formats: multiple-choice questions and those requiring students to construct their response. The actual tasks were arranged in half-hour clusters (each student having to complete four clusters) in 13 booklets, with each cluster appearing in each of the four possible locations in the booklets (OECD, 2007). Additionally, students answered a 30-minute background questionnaire, providing information about themselves and their home. School principals were also given a 20-minute questionnaire about their schools. Specific to PISA 2006, two optional questionnaires were offered, one dealing with the use of computers and technology in the schools at the student level and one asking parents to provide background information on scientific literacy and feelings of the importance of science in their children's education (OECD, 2006).

Measurement, Reliability, and Validity of the PISA Data Set

The design and implementation of a valid, reliable, and comparable assessment of key competencies at the international level are time-consuming, expensive, and risky endeavours (Murray, 2003). Because conducting international studies that are fair, meaningful, and useful—which it is hoped includes PISA—is such a challenging undertaking, there are, as might be imagined, a number of criticisms of international assessment in general and PISA specifically within the literature. These criticisms share much common ground and can be considered within three main contexts: the original philosophical and methodological approach, the content within the measures, and the further analysis and interpretation of the results.

Approach. The extent of and interest in international comparative studies has grown

considerably over the past few decades as it has become more important for politicians to know how their country is doing in global knowledge (Donlin, 2007). PISA is embedded in the overall political and economic aims of the OECD (i.e., growth in market economies and free trade) and results and rankings shape international educational policies and influence national policies in most participating countries (Sjoberg, 2007). The use of the results from PISA with academic research is recognized as an important corollary activity (see Goldstein & Thomas, 2008; Marks, 2005; Prais, 2003). PISA has garnered significant attention from the public and educators by generating data to enhance the ability of policy makers to make decisions based on evidence (Bussiere, Cartwright, & Knighton, 2004). However, it is also important to recognize that PISA is not meant to be an academic research undertaking, as it is a commissioned, research-based survey formulated by closed groups with strong influence from the administrative layers of education ministries (Donlin, 2007) and should be judged based upon the agenda of the OECD.

Content. In a comparative test, reliability—the consistency or repeatability of a measure—is important as countries must be appraised in the same way. Reliability concerns within PISA include the lack of comparability to earlier studies, the sample (e.g., schools that drop out and the possible inequality of their substitutes, the potential for the dropout rate of students by age 15 not being random, and the failure to include the classroom-level factors where education actually takes place), and the difficulty in appropriate wording for questions across countries (i.e., translation) (Langfeldt, 2007). Where PISA goes to great length to ensure multiple translations from both English and French original versions, some things that are culturally and educationally specific defy all attempts at exact translation (Goldstein, 2004).

Validity is concerned with the instrument measuring what is intended and is a significant issue in the social sciences, because methods of measurement are primarily indirect (Frankfort-

Nachmias & Nachmias, 1996). PISA's attempts to measure how well students cope with real life situations using what they have already learned, as opposed to the more traditional school curriculum, is criticized on the grounds of construct validity (Prais, 2003). He argues that PISA's efforts do little more than confirm the difficulty of framing "real life" questions that are equally appropriate for participants across multiple nations and social backgrounds. The fundamental question regarding validity is whether one can reasonably claim that sitting with a paper and pencil test and answering questions about imaginary situations has anything to do with competencies in the sense that one normally understands them (Donlin, 2007). Additionally, the difficulty in defining scientific literacy also adds to the challenges with validity (see Chapter 2).

Further analysis. Significant concerns with PISA can be compiled into three issues. First, the time frame for development and administration of PISA is a short three years, taking only half the time of the TIMSS survey (Rochex, 2000). Second, this haste results in a lack of transparency, as only specific institutions are selected for the process of creating the measure. This centralized focus made it difficult for interested parties to discern the political from the scientific parts of the process (Rochex, 2000). Third, from each of the three aspects of literacy, a single score is derived from item response theory (IRT) on the assumption of a single underlying dimension (Donlin, 2007; Goldstein, 2004). The construction of each subscale was based upon IRT and only accepted those items that fit the one-dimensional model across a variety of countries, and those items that did not were excluded (Goldstein, 2004). This has the benefit of allowing for one-dimensional simple ranking in league tables but constrains the measurement model of literacy and excludes important information. As Goldstein commented, "if the true aim is to better understand the underlying differences between countries and to explore data that might shed light on these differences, then the reflection of multiple dimensions might better suit

this need" (2004, p. 323). Similarly there still remains a lack of critical appraisal of the methodological approach to PISA, of the findings and of the ultimate aims of the study, which is not conducive to a better understanding of the outcomes of education (Prais, 2003).

PISA addresses these criticisms specifically and generally. Specifically, McGraw (2008) addresses the timing issue by recognizing that the OECD had become involved in collecting its own education data prior to PISA through its International Adult Literacy Survey (IALS). This previous experience and linkage to the IALS made the process move more quickly than if it was starting from scratch. He further argues that the psychometric models used in PISA were chosen because they enable the development of performance scales that permit substantive descriptions of competencies as well as the opportunity to monitor change over time.

PISA generally addresses criticisms by arguing that they apply the following checks: quality assurance for translation, administration, and sampling; cultural and linguistic breadth through an iterative process where participating countries both develop and revise items; and appropriate data handling and analysis (OECD, 2006). PISA was developed collaboratively by OECD nations, agreed upon by participating countries, and implemented by national organizations. Through the co-operation of participating nations and the combination of these above steps, PISA produces high quality instruments and outcomes with high levels of validity and reliability particularly well suited for improved understanding of education systems as well as students' knowledge, skills, and attitudes (OECD, 2006). After each round, a technical report is published by the OECD, providing documentation of the procedures used in all phases of the survey, giving support that this measure has been consistently and appropriately conducted.

Additionally, the design and technical specifications of PISA meet the requirements of a good study as laid out by Beaton et al. (1999) for judging quality in large-scale international

studies of educational achievement. These guidelines are as follows:

1. The aims of the PISA study are clearly presented as well as the rationale for going beyond the traditional curricula measures;
2. The study is transparent in design and employs a variety of individuals and international organizations in a highly iterative process;
3. The target population is identified for the purpose of collecting data on students at the end of formal education;
4. Sampling procedures are appropriate;
5. Item construction, although not linked to curriculum, went through an extensive selection process, and items were field trialed and further analyzed via various Rasch (a 1-parameter IRT analysis) fit statistics;
6. Data are collected via a National Project Manager (NPM) in each participating country and analyzed to allow the ability measures to be linked to the variety of background and demographic variables collected; and finally,
7. The results are reported within each assessment domain emphasizing the profile of student responses in each country (p. 49).

PISA Test Analysis

Rasch model item response theory. As the three main areas PISA assesses (i.e., reading, mathematics, and science) are comprehensive areas in education, for the measure to be valid, a large number of items are required (OECD, 2005). However, PISA also needs to be sensitive to overburdening the students who write the measures (as fatigue can possibly bias results) and to not require schools to sacrifice an inordinate amount of instructional time to the measure. In order to balance these needs, students are required to complete a sub-set of the item pool. This is

referred to as an incomplete design. To provide item-level information to communicate the results of this survey, some summarization must be provided (OECD, 2005).

In order to estimate scores on a common metric, PISA uses a one-parameter IRT scoring and analysis model (Hambleton & Swaminathan, 1985). This one parameter or Rasch model is used to determine the probability of a specified right/wrong response modeled as a function of person and item parameters to estimate a student's ability. The Rasch model uses the number of correct answers and the difficulty of the items administered to a student to estimate ability (OECD, 2005). As all items in PISA have been pre-located on the same continuum, ability estimates can be estimated for students who did not write the same questions. This is accomplished through linking items—having students completing common items. PISA separates the entire item pool into 13 clusters, and from this, 13 booklets are created, each comprised of 4 clusters (OECD, 2005). The development team reasons that as the difficulty of clusters changes among booklets, the requirements of the linking process are met.

Survey design weights. The base PISA target population in each country consists of 15-year-old students enrolled in educational institutions within each country participating in the survey. The sampling design used for PISA is a two-staged stratified sample where the first stage of the sample consists of individual schools having 15-year-old students, and in the second stage, thirty-five 15-year-old students are sampled from each selected school. Again, 150 schools (or all) are selected in each country, and thirty-five 15-year-old students from each school complete the survey (OECD, 2002).This design was selected, similar to other international studies of this kind, because census data is often difficult to secure, too expensive for such a large population, too time consuming, and does not necessarily aid in securing any more information than can be achieved through the sample (OECD, 2002).

However, in pursuing designs such as the one in PISA, the potential for bias in the sample is real, as each student does not have the same probability of being selected. Population parameters need to be estimated by taking these varying probabilities into account. For example, some schools and/or students may not want to participate, information might be out of date, or absenteeism may cause a problem. Similarly, if students do not have the same chance of being selected, population parameters estimated from these procedures may result in bias. To accommodate for some of these potential difficulties, PISA sets the minimum participation rate for schools at 85% and for students within schools at 80% (OECD, 2002).

Because the PISA sample design does not give each individual in the population an equal chance of being selected (i.e., individuals or groups could be under-represented) (OECD, 2002), the data have to be weighted to insure sample statistics accurately represent the population. "Survey weights are required when analyzing PISA data" (Willms & Smith, 2005, p. 11), primarily to calculate appropriate estimates of sampling error and to make valid inferences and estimates. PISA calls for over-sampling and under-sampling within countries (e.g., Canada), and design weights are used to weight students differently such that the bias in the sample is reduced. Ideally, the role of the design weights are to reduce if not eliminate these biases by weighting students differentially.

Estimation of Measurement Error

Plausible values. Plausible values are values that resemble test scores and are computed to have approximately the same distribution as the latent trait being measured (Wu, 2005). They represent the range of ability that a student might reasonably have, given the student's item responses, and they allow for the empirical estimation of measurement error in the ability scores. The OECD (2005) defines them as values that represent the range of abilities that a student might

reasonably display and that are used, along with replicate design weights, in the analysis to calculate accurate estimates of country level standard error. These values were developed as a computational approximation to obtain consistent estimates of population characteristics in assessment situations—like PISA's rotated-booklet design—where students are administered too few items to allow for precise estimates of their ability (Willms & Smith, 2005). Because each student does not complete the entire survey, plausible values represent a sample of ability estimates from the distribution of scores that the student might have obtained had he or she completed the full test, while accounting for measurement error associated with the test. Again, in the words of the OECD, plausible values consist of "mathematically computing distributions (denoted as posterior distributions) around the reported values and the reported length in the example and assigning to each observation a set of random values drawn from the posterior distributions" (OECD, 2005, p. 73). The five plausible values in PISA provide information about a student's ability estimate as well as the uncertainty associated with that estimate (Wu, 2005).

Countries To Be Examined in This Study

The data in the PISA data sets is hierarchical; there are data for students and for the schools in which the students learn. The breadth of variables from the wide range of countries in this data set allows researchers to explore questions that would not be possible in traditional research, where one researcher or a small team of researchers collect their own data. The data set also lends itself to more complex data analysis, such as hierarchical linear modelling (HLM), which is described more thoroughly in the data analysis section of this chapter.

The initial research questions look at scientific literacy for all nations in PISA 2006; however, for the HLM portion of the study, the relationship between science self-beliefs, socio-economic status and immigrant status and academic achievement for the countries of Australia,

Canada, Germany, New Zealand, Spain, and the United States are modeled for all domains. The rationale for choosing these six countries for comparison is simply that the United Nations, in its most recent report on world population, has identified Western Europe, North America, and Oceania as major destinations of net migration (UN, 2006). These counties are representative of those regions that will receive the majority of these immigrants, and thus they were included in the study.

The Variables of Interest

Once the OECD PISA survey has been implemented and the data collected, tabulated, and analyzed, the OECD produces a great deal of material in the form of publications (e.g., PISA 2006 Science Competencies for Tomorrow's World), manuals (e.g., FAQ: OECD PISA) and reports (e.g., Reports produced by participating countries – PISA 2003). These materials are open and accessible to the public and support the original mandate to provide policy-oriented international indicators of the skills and knowledge of 15-year-old students. What is also useful and applicable within this discussion is that the OECD makes available to interested parties the data set related to student performance, information on student attitudes, and approaches to learning as well as the learning environment and organization of schools.

Scientific Literacy

There were 37 science units, comprising a total of 108 cognitive items and 31 embedded attitudinal items representing 210 minutes of testing time for science in PISA 2006 (OECD, 2009). The main study items were allocated to thirteen item clusters (seven science clusters, two reading clusters, and four mathematics clusters) with each cluster representing 30 minutes of test time. The items were presented in thirteen test booklets with each booklet composed of four clusters. PISA 2006 measured scientific literacy across a continuum of students' demonstrated

knowledge of scientific facts and principles as well as their ability to apply these to contextual problems. Individual student scores were reported in each of the three identified competencies (i.e., identifying scientific issues, explaining phenomena scientifically, and using scientific evidence) and for overall science performance. Scientific performance scale scores were constructed so that the average student score in OECD counties was 500 and approximately two thirds of students scored between 400 and 600, with a standard deviation of 100.

Item response models can be used to generate estimates of student ability (θ) and item difficulty on the same scale. For example, a student with a score of 650 is expected to correctly answer a question at this level as well as those questions below it (OECD, 2006). In addition, performance scores and item difficulty were defined and specified for PISA 2000, 2003, and 2006 according to six proficiency levels—with one as the lowest and six as the highest—that described the types of competencies possessed by students at each level (OECD, 2006).

Scientific literacy is defined in PISA as a continuum from less to more literate, with a less developed individual limited to factual knowledge and a more literate student able to model, predict, and explain. PISA 2006 also more clearly differentiated science literacy from reading literacy (by reducing the reading load for scientific questions) yet maintained some overlap through the 108 science items, of which 22 were common to PISA 2003 and the remaining 86 items selected from a pool of 222 newly developed ones (OECD, 2009). Scientific literacy in this assessment is characterized by four interrelated aspects: context (recognizing situations involving science and technology), competencies (identifying, explaining, and concluding), knowledge (about the natural world and science itself), and attitudes (interest in science and motivation to act responsibly). Item formats with cognitive items were multiple choice, short closed response, and open constructed response. Attitudinal items required students to express their level of

agreement on a four-point Likert scale following statements regarding either an interest in or support for science.

PISA Approach to Measuring ESCS (SES), Immigration, and Attitudes Toward Science

Economic, social, and cultural status (ESCS). It is well known that students from less advantaged home backgrounds tend to, on average, do less well at school than their more advantaged peers (OECD, 2007). An understanding of how this disadvantage is mitigated between countries has the potential to indicate how well school systems manage to provide opportunity for students despite background influences. In general, educational outcomes have been shown to be influenced by family background in many different and complex ways (Shah, 1997, as cited in Schulz, 2005).

Socio-economic status (SES) is an important explanatory factor in numerous disciplines, including education (Schulz, 2005). It is also accepted that differences in economic capital create differences in school performance as schooling outcomes have been shown to relate to the SES of a child's parents (Turmo, 2004). PISA asks 14 questions pertaining to students' family background, including the occupation of mother and father, parental education, and home possessions (e.g., desk for study, books of poetry, dishwasher), family structure (adult presence at home), and immigrant background (place of birth) (OECD, 2005a). PISA does not measure financial resources directly; however, the data do provide an index of economic, social, and cultural status designed to capture student, family and home background as well as occupational status (OECD, 2005a). The index is derived from the variables: the highest international socio-economic index of occupational status (HISEI), the highest level of education of the student's parents (HISCED) converted into years of schooling, and the index of home possessions (HOMEPOS) (a proxy for income in the home). The questions asked were not randomly chosen,

but are derived from a theoretical framework to provide evidence of a student's socio-economic status (OECD, 2005a).

Because some of the indices used in PISA 2006 are components of responses from students, principals, or parents the questions aggregate to represent larger constructs based on theory and research (OECD, 2005b). Most questionnaire items were scaled using a one-parameter IRT methodology (OECD, 2009). Structural equation modeling was used to confirm the theoretically expected behaviour of the indices and to validate their comparability across countries (OECD, 2005a). The index of ESCS was scaled by PISA using a weighted maximum likelihood estimate (WLE) (Warm, 1985, as cited in OECD, 2005b) employed to produce less biased parameter estimates required for IRT. ESCS was further scaled from equal-sized sub-samples of students from each OECD country, anchored for all students and schools and then standardized with the mean OECD student population at zero and the standard deviation at one (OECD, 2005a).

Using these three components for deriving a composite index of socio-economic status is in line with the literature (Schulz, 2005). The student ESCS scores are derived from the factor loadings of a principal component analysis for the three ESCS components. The factor loadings are the correlation coefficients between the variables (rows) and factors (columns) (Garson, 2009). Analogous to Pearson's r, the squared factor loading is the percent of variance in that indicator variable explained by the factor. These three components were: the highest international socio-economic index of occupational status (HISEI) (.72–.87), the highest international standard classification of education (HISCED) converted into years of schooling (PARED) (.73–.86), and home possessions (the number of books at home as well as home educational resources [HEDRES] and cultural possessions [CULTPOSS]) (HOMEPOS) (.55–.83), as well as the

reliability index (.52–.80) (OECD, 2005a). Comparing ESCS mean scores per country across PISA 2000 and PISA 2003 shows a very high correlation of .96 (Schulz, 2005).

Parental occupation, as gathered through the demographic data by asking students to report on parental occupations, is converted into a four-digit ISCO (International Standard Classification of Occupations) code (ILO, 1990, as cited in Schulz, 2005; OECD, 2005) and then converted into a socio-economic index of occupational status (Ganzeboom, de Graaf, & Treiman, 1992, as cited in Schulz, 2005). Three indices are obtained from these scores: the father's, the mother's, and the highest occupational level. The highest international socio-economic index of occupational status corresponds to the highest international socio-economic index of occupational status of either the father or mother.

Parental education is based on categories replicating the coding of ISCED (International Standard Classification of Education). ISCEDL refers to the highest ISCED between the two parents and has six categories: zero for no education, one for the completion of primary education (ISCED level 1), two for the completion of lower secondary education (ISCED level 2), three for the completion of vocational/pre-vocational upper secondary education (ISCED level 3B or 3C), four for the completion of upper secondary education and/or non-tertiary post-secondary (ISCED level 4), five for qualifications in vocational tertiary (ISCED 5B), and six for completion of tertiary-type A and advanced research programs (ISCED levels 5A and 6).

PISA included 13 items of home possessions (e.g., desk for study, books of poetry, dishwasher) as well as three country-specific items due to specific situational and cultural differences. An index of home possessions was derived as a summary index of all household items plus a dummy variable indicating more than 100 books at home. The items were scored as dummy variables so that positive IRT scores indicated higher numbers of home possessions

(Schulz, 2005). Scale reliabilities of these home possession indices are included in Table 1.

Table 1

Scale Reliabilities of Home Possession Indices of ESCS

Variable	OECD mean	Australia	Canada	Germany	New Zealand	Spain	United States
WEALTH	0.62	0.60	0.61	0.64	0.67	0.64	0.70
HEDRES	0.49	0.60	0.40	0.47	0.61	0.45	0.65
CULTPOSS	0.61	0.61	0.63	0.61	0.67	058	0.66
HOMEPOS	0.64	0.62	0.64	0.62	0.69	0.64	0.74

Home educational resources (HEDRES) is a noticeably lower reliability, and this was also observed in the PISA 2000 results (OECD, 2009).

Immigrant background. This simple index was defined by PISA as the country of birth of students and their parents. PISA did not intend for this variable to encompass aboriginal people in Canada, the United States, Australia, and New Zealand. The immigration information a student provides indicates the countries where the student and his/her parents were born in order to classify students into three categories: native students (those who were native-born or who had at least one native-born parent), first-generation students (those who were foreign-born with foreign-born parents), and second-generation students (those who were born in the country but whose parents were both foreign born).

Science self-beliefs. PISA 2006 has devoted considerable time in the survey toward collecting data on students' attitudes and engagement with science. Eight items measuring students' science self-efficacy (under the conditions of performing a science task) were included (OECD, 2009). These items were scaled so that positive scores on this new index for PISA 2006 indicate higher levels of self-efficacy for science. Six items measuring students' science self-concept were included in the student questionnaire. Again, positive scores on this index for PISA

2006 indicate higher levels of self-concept for science.

Table 2

Scale Reliabilities of Science Self-efficacy and Science Self-concept

Variable	OECD mean	Australia	Canada	Germany	New Zealand	Spain	United States
Science self-efficacy	0.83	0.88	0.85	0.82	0.87	0.83	0.87
Science self-concept	0.92	0.93	0.94	0.90	0.92	0.92	0.93

Table 2 shows internal consistencies for the two science self-belief scales. Both constructs have high reliabilities across selected countries with self-efficacy typically around .85 and self-concept just over .90.

Data Analysis

Descriptive Statistics

Initially, all independent and outcome variables were descriptively analyzed and displayed (i.e. tables, histograms). Assumptions of normality were assessed between the independent variables as well as with the outcomes measure to assure no problems of multicollinearity exist.

Explorations of School- and Country-Level Self-concept, Self-efficacy, and Science Achievement

Univariate, bivariate and multivariate techniques were used to investigate the relations between science self-concept, science self-efficacy and science achievement. Kifer (2002) presented geographic effects associated with self-concept in the TIMSS study and an extension of this to science self-concept and science self-efficacy, as measured by PISA 2006, is proposed

here. Means and standard deviations for science self-concept, science self-efficacy and science achievement by country as well as within-country correlation was calculated. The exploration sought to determine if there are geographical patterns (i.e. South Asian countries with higher achievement but lower reported self-concept) within the findings. One approach to answering this question at the country level is through ranking the countries by both average science self-concept and science self-efficacy and then comparing the achievement to the upper and lower half (i.e., creating a median split). Similarly, student level science self-concept and science self-efficacy correlations with science achievement can be calculated by using within country sampling weights (Wilkins, 2004). The question to be answered here is what within country relationship across the countries which participated in PISA 2006 might exist between both science self-concept and science self-efficacy and science achievement?

Multiple Regressions for Components of ESCS

One possible approach to studying the relationship between students' scientific literacy and SES is to look at the constructs which make up the ESCS in PISA 2006 (see Table 3). As these constructs are anticipated to be highly correlated, multiple regression analysis is a relevant approach to studying how much of the variance in scientific literacy can be explained by combinations of these constructs (i.e. how much does cultural capital, social capital, economic capital and the PISA variable ESCS contribute to predictions of students scientific literacy?). The focus on this section is on the squared multiple correlations (R^2) – as results of regression with overlapping variance can be difficult to interpret. The R^2 value can be understood as the total variance explained by the combined independent variables in the model (Turmo, 2004). In this way, the R^2 values for cultural, social and economic can be calculated for each country in the study to uncover if one accounts for a larger share of variance for scientific literacy for PISA

2006. Finally, a regression equation was calculated for science literacy predicted by ECSC for each country (all 57) in the entire PISA 2006 survey.

Multiple regression equation for science literacy predicted by the indicators of economic, cultural and social capital – as well as the composite ESCS – are listed below:

$$Science_i = \beta_0 + \beta_1(WEALTH) + \beta_2(HOMEPOS) + r_i$$

$$Science_i = \beta_0 + \beta_1(CULTPOS) + \beta_2(BOOKS) + \beta_3(ISCED) + r_i$$

$$Science_i = \beta_0 + \beta_1(HEDRES) + \beta_2(HISEI) + r_i$$

$$Science_i = \beta_0 + \beta_1(ESCS) + r_i$$

where $Science_i$ is the science score for student *i*;

β_0 is the intercept for science score;

$\beta_{1...3}$ are the regression coefficients that weight the predictors in the regression analysis;

r_i is the residual error.

Table 3

Definitions of Variables in Multiple Regression Equations for Science Literacy

Variable	Definition
ESCS	Index of economic social and cultural status
HISEI	Index of highest index of occupational status
HOMEPOSS	Index of home possessions
WEALTH	Index of family wealth
CULTPOSS	cultural possessions
HEDRES	Index of home educational resources
ISCEDL	highest educational level of parent
ST15Q01	number books in the home

The rationale for the placement of indicators under associated constructs equates back to

the original ESCS measure in PISA. Inside the PISA 2006 survey, those questions relating to cultural capital (i.e. attitudes and knowledge needed to succeed in the current educational system a student has which are provided by parents [Turmo, 2004]), are identified (see Table 4). Similarly, social capital, those resources based on group membership, relationships and networks (Croll, 2004) and economic capital, command over economic resources, are also identified under the appropriate heading in Table 4.

Table 4

Constructs in PISA 2006 Related to SES and Cultural, Social, and Economic Status

Economic capital	Cultural capital	Social capital
Family wealth	Cultural possession in the home	Home educational resources
Index of home possessions	Books in the home	Highest parental occupation
	Highest education level of the parent	

However, standard regression presents some problems with the PISA 2006 data set. As previously mentioned PISA is nested data and thus violates the assumptions required for multiple linear regression if school level predictors are included in the analysis (i.e. selecting students attending the same schools cannot be considered as independent observations). It follows that "the uncertainty associated with a population parameter (e.g. standard error) will be greater for a two stage sample than for a simple random sample of the same size" (OECD, 2005b, p.39). So, because students sampled from the same school will be more similar than those in different schools, the resulting standard errors will be too small resulting in an inflated significance level (Hox, 1995). Willms and Smith (2005) recommend that estimations of the sampling variance for each plausible value should employ a Jackknife or Balanced Repeated Replication (BRR) procedure (for PISA this translates to conducting the analysis 400 times or 80 times for each of the 5 PV's). The OECD has provided replicate weights in the dataset and macros for Statistical Analysis Software (SAS) to accommodate for this issue that will be employed for much of this study. Additionally, population statistics (i.e. correlation coefficients) should be further estimated using each of the five calculated plausible values separately and then averaged (OECD, 2005a). In this way, the R^2 values for cultural, social and economic capital can be calculated for each country in the study to uncover if one is a larger predictor of scientific literacy for PISA 2006.

Hierarchical Linear Modeling for Spain, Germany, Canada, the United States, Australia, and New Zealand

Hierarchical linear modeling (HLM) (Byrk & Raudenbush, 2002) is a data analysis technique used to address hierarchical data structures that is a more advanced form of simple and multiple linear regression (Snijders & Bosker, 1999). Compared to classical regression, multilevel (hierarchical) modeling is useful for data reduction and essential for prediction (Gelman, 2006). The basic model, interpretation and application to PISA of HLM will be further explored in this chapter.

One of the assumptions underlying traditional regression is that observations of one individual are not systematically related to those of another (Luke, 2004; Willms, 1999). This assumption is violated with data such as PISA when student level and school level data are combined into an analysis and as such, a traditional regression approach will result in standard errors that are too small and in biased estimates. Multilevel analysis allows variance in outcome variables to be analyzed at multiple hierarchical levels, between-group and within-group; thus, HLM is appropriate for use with nested data such as PISA 2006.

The goal of multilevel analysis is to predict values of some dependent variable based on a function of predictor variables at more than one level (Luke, 2004). In the PISA situation, HLM uses level-1 student and level-2 school variables to help explain variation in achievement scores while accounting for the variance at each level. HLM allows for estimating both the effects of group-level variables on school mean score and on the slopes of the individual characteristics to predict outcome variables (Willms & Smith, 2005). HLM is also potentially useful here for its ability to include in the analysis both sample weights and plausible values, both of which are employed in all PISA analysis. Sample weights are used to account for the stratified sample

design in PISA and also to ensure that population parameter estimates are unbiased. The purpose of assigning different weights to students is to give appropriate estimates of sampling error, to make valid estimates and inferences, and to avoid or reduce the biases due to the unequal selection probabilities in the two-stage stratified sampling in PISA (OECD, 2005). The dependent variable in a multilevel analysis PISA 2006 is defined as the overall scientific literacy performance which is reported as five plausible values chosen for each student. Plausible values in PISA 2006, simply the value selected from the estimated distribution of each student's ability estimate, were derived from a Rasch analysis (OECD, 2005).

Null models. The first step in the multilevel analysis will be to determine if a multilevel model is required in the first place. In general one can use three types of justification for a multilevel model: empirical, statistical and theoretical (Luke, 2004). The simplest argument for multilevel modeling is that because so much of what we study is multilevel in organizational structure (e.g. students in schools) we should use theories and techniques that accommodate for this reality (i.e. linear regression assumes normality of variance across samples where HLM does not). The other reasons would be to avoid the risk of making either an ecological fallacy (where relationships for groups are assumed to hold for individuals) or the opposite atomistic fallacy (where inferences about groups are incorrectly drawn from individual-level data) (Hox, 1995; Luke, 2004). The most formal piece of empirical evidence is provided by the intraclass correlation coefficient (ICC), a measure of the proportion of variance in the dependent variable accounted for by the level-2 units (Snijders & Bosker, 1999). This can be accomplished most easily by constructing the null model for Spain, Germany, Canada, America, Australia and New Zealand in order to estimate the proportion of variance in the outcome measure that can be attributed to level-2 (the schools).

The null model is as follows:

Student level: $Science_{ij} = \beta_{0j} + r_{ij}$

School level: $\beta_{0j} = \gamma_{00} + u_{0j}$

where $Science_{ij}$ is the science score for student i in school j;

β_{0j} is the average science score in school j;

r_{ij} is the error of using mean science score in school j to predict the science achievement of student i in school j;

γ_{00} is the grand (overall, across-school) mean of science scores;

u_{0j} is the error or unique school effect of using grand mean science score to predict the average science score in school j.

The outputs of null models can be used to (1) evaluate whether the school mean science scores (β_{0j}) vary across schools; (2) estimate the proportion of total variance explained in school level (i.e. intraclass correlation ρ); and (3) estimate the grand means of science scores (γ_{00}) in Spain, Germany, Canada, America, Australia and New Zealand.

Random coefficient models. The next step involves moving from the simple to more complex models. Although there is no single way to best build a multilevel model, the individual steps should be based upon the a priori hypothesis. However, the typical path is to build the model from the bottom up (Luke, 2004) and to start with level-1 predictors. In this case, this step includes adding the variables economic, social and cultural status (*ESCS*), immigrant status (*Non-native*), self-efficacy (*SCIEEFF*) and self-concept (*SCSCIE*) – which answers the research question concerning the variability in science achievement that can be further explained by these variables. The HLM is as follows.

Student level:

$$Science_{ij} = \beta_{0j} + \beta_{1j}(ESCS)_{ij} + \beta_{2j}(Non-native)_{ij} + \beta_{3j}(SCIEEFF)_{ij} + \beta_{4j}(SCSCIE)_{ij} + r_{ij}$$

School level: $\beta_{0j} = \gamma_{00} + u_{0j}$

$$\beta_{1j} = \gamma_{10} + u_{1j}$$

$$\beta_{2j} = \gamma_{20} + u_{2j}$$

$$\beta_{3j} = \gamma_{30} + u_{3j}$$

$$\beta_{4j} = \gamma_{40} + u_{4j}$$

where Non-nuclear, and Non-native are dichotomous dummy variables;

β_{2j} to β_{4j} is the mean differences between the science achievement of the 0 and 1 groups in the dichotomous student-level variables;

γ_{10} to γ_{40} are the across-school slope averages;

u_{1j} to u_{4j} are the errors to the intercept and level-1 gradients associated with school j.

The proportion of variance explained by adding level-1 predictors into the student-level can be derived from the difference of the variance within school between this model and that of null model. The presence of school level error terms (u) for each student-level variable is included to evaluate whether significant variation exists between schools on that coefficient. In other words, individual differences associated with each student level variable may be different across schools.

Intercepts- and slopes-as-outcomes model. Once the level-1 model is established (i.e., non-significant predictors are removed), potential level-2 predictors may then be added to the

model. The level-2 predictors selected for the analysis (i.e., school ESCS and school proportion of immigrants) were based upon prior research. Marks (2005) uncovered that in many countries on PISA 2000, SES account for the weaker performance of immigrants. The traditional contextual model (i.e., school-level variables are aggregates of student-level ones), was selected because these contextual effects bear important implications for educational policy (O'Connell & McCoach, 2008). For example, students with low SES may be disadvantaged twice in their academic achievement, once for low SES and once for attending schools with low SES – as is often the case. By identifying significant influence of these school level predictors on the conditioned mean as well as the student level slope coefficients, contextual level relationships can be uncovered. It is anticipated that an increase in either of these variables will influence the student level in differing directions. If this proves accurate, policy intervention that can reduce the impact of SES on academic achievement will have the added benefit of improving academic achievement for immigrant groups.

The intercepts- and slopes-as-outcomes model allows us to model the variability of the regression coefficients (both intercepts and slopes) (Byrk & Raudenbush, 2002).

Student level:

$$Science_{ij} = \beta_{0j} + \beta_{1j}(ESCS)_{ij} + \beta_{2j}(non-native)_{ij} + \beta_{3j}(SCIEEFF)_{ij} + \beta_{4j}(SCSCIE)_{ij} + r_{ij}$$

School level: $\beta_{0j} = \gamma_{00} + \gamma_{01}(school\ ESCS) + \gamma_{02}(proportion\ of\ non-native) + u_{0j}$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}(school\ ESCS) + \gamma_{12}(proportion of\ non-native) + u_{1j}$$

$$\beta_{2j} = \gamma_{20} + \gamma_{21}(school\ ESCS) + \gamma_{22}(proportion of\ non-native) + u_{2j}$$

$$\beta_{3j} = \gamma_{30} + \gamma_{31}(school\ ESCS) + \gamma_{32}(proportion of\ non-native) + u_{3j}$$

$$\beta_{4j} = \gamma_{40} + \gamma_{41}(school\ ESCS) + \gamma_{42}(proportion of\ non-native) + u_{4j}$$

In each step, the decision as to which fixed coefficients, (co)variates and random terms to retain will be assessed based upon the school- and student-level variable significance, the change in the deviance and changes to the variance components (Hox, 1995). After each change this HLM iterative model will be rerun to acquire the next and potentially final model. The results of $\gamma_{01},\cdots,\gamma_{02}$ and $\gamma_{11},\cdots,\gamma_{22}$ demonstrate which school-level variables explain school mean science achievement and which school-level variables influence the gradients of student factors on science achievement. Additionally, they provide information on evaluating the student level error variance (τ's) index of significant variance in the coefficients (β) across schools. Tau (τ) represents the variance of the $u's$ on the intercept and on each level-1 predictor. By comparing Tau (τ) estimates across models an index of proportional reduction in variance or "variance explained" at level-2 can be developed (Byrk & Raudenbush, 2002). This information can be used to answer the last research question as this study will compare the different results of these final HLMs for Spain, Germany, Canada, the United States, Australia and New Zealand.

Ethical Approval Procedures

Pursuant to the requirements of the Human Ethics Research Board of the Office of Research Services at the University of Victoria, an Ethical Waiver was applied for and approved for this study so that PISA data might be analyzed to explore the research questions for this dissertation (see Appendix A).

Chapter 4: Results

The results from this analysis are presented here in the univariate, bivariate and multilevel statistical form. Descriptive statistics for all variables of interest will initially be presented. The first research questions will be explored with zero order correlations for either self-efficacy or self-concept and science achievement across all nations that participated in PISA

2006. Overall relationships between science self-concept, science self-efficacy and science achievement by classroom environment will also be determine through correlation analysis. The second research focus will regress the impact of differing forms of capital (i.e. economic, social and cultural) on the outcome of scientific literacy to uncover if one is a larger predictor of scientific literacy for PISA 2006. Finally, a series of Hierarchical Linear Models (HLM) will be constructed to predict science achievement from school and student level predictors of SES, immigrant status and science self-beliefs (i.e., science self-concept, science self-efficacy) across the nations of Australia, Canada, Germany, New Zealand, Spain and the United States

Descriptive Statistics

Student Participants and Country Samples

In total 398,746 students from 14,365 schools in 57 countries around the world participated in the PISA 2006. The students were aged between 15.2 and 16.3, including 197,268 females and 201,478 males. These statistics are generally consistent with the PISA sampling standards concerning the age of participants and the equal size of gender groups. Consequently, there is no obvious violation to the sample representation. An abridged sample of nations (those selected for the multilevel analysis) as well as the overall descriptive statistics for the combined student and school sample for all nations involved in the PISA 2006 sample is presented in Tables 5 and 6.

Table 5

Abridged Descriptive Statistics of Student and School for in PISA 2006

		Total	Age		Gender	
		N	Years		*N*	
			Min	Max	M	F
Australia	Students	14,170	15.2	16.3	7,192	6,978
	Schools	356				

Canada	Students	22,646	15.3	16.3	11,104	11,542
	Schools	896				
Germany	Students	4,891	15.3	16.3	2,491	2,400
	Schools	226				
New Zealand	Students	4,823	15.3	16.3	2,350	2,473
	Schools	170				
Spain	Students	19,604	15.3	16.3	9,803	9,801
	Schools	686				
United States	Students	5,610	15.3	16.3	2,839	2,771
	Schools	278				

Table 6

Abridged Overall Descriptive Statistics of Student and School for All Nations in PISA 2006

	N	Gender		Min	Max	Range	Mean
		M	F				
Students	398,746	201,478	197,268	339	30,971	30,632	7,057.98
Schools	14,365			12	1,140	1,128	256.93

Interpreting PISA Index Scores

The following section provides descriptive statistics for the independent and dependent variables used in this study. Some of these variables (as indicated) are reported as composite indices which summarize student or school representative responses to a set of related questions (OECD, 2006b). Several of these indices reflect larger constructs on the basis of theoretical considerations and previous research and are derived from a comparison of scores across countries using structural equation modeling (SEM). Where an index involves multiple questions and responses, the index was scaled using a weighted maximum likelihood estimate (WLE) and a one-parameter item response model (Warm, 1985, as cited in OECD, 2005b). For each index, a student with an average level (determined as an average across OECD countries) is given a value of zero. About two thirds of the total OECD student population reported values that fall between -1 and 1 on the scale (i.e., each index has a standard deviation of 1). This means that a negative value on the index does not necessarily mean that students responded negatively to the items that make up the index; rather, a negative index value means that students responded lower than the average OECD student. Similarly, positive scores mean that students responded higher than the average OECD student (OECD, 2006b).

Student-Level Variables

Student background. The PISA index of *economic, social and cultural status* (ESCS) was created to capture wider aspects of a student's family and home background in addition to

occupational status of parents. It was derived from: the *highest index of occupational status* (HISEI) of the father or mother; the index of *highest educational level of parent* (ISCEDL) converted into years of schooling and the index of *home possessions* (HOMEPOSS) – students' own room, items in their home and country specific items. Additional indices used in this study included *family wealth* (WEALTH), *cultural possessions* (CULTPOSS), and *home educational resources* (HEDRES) obtained by a series of student level questions concerning materials in the home (some of which were specific to nations in the study). As no direct measure on parental income was available from PISA, access to relevant household items was used as a proxy. Scale construction for all items was performed through IRT scaling. The student scores on the index are factor scores derived from a Principal Component Analysis (PCA) and standardized with an OECD mean of zero and standard deviation of one (OECD, 2006b). One other measure referenced at the student level was a categorical measure of the numbers of books in the home (ST15Q01) and was coded as: 1-0 to10; 2-11 to 25; 3-26 to 100; 4-101 to 200; 5-201 to 500 and 6-more than 500. The descriptive statistics of these student background variables for all countries are displayed in Table 7 and country level data in both descriptive form and histogram are in Appendix B and C.

Table 7

Descriptive Statistics of Student Background Variables for All Countries in PISA 2006

Variable	*N*	Min	Max	Mean	SD
ESCS – *economic social and cultural status*	394,837	-5.67	3.35	-0.43	8.82
HISEI - *highest index of occupational status*	377,402	16	90	46.41	129.88
HOMEPOS - *home possessions*	396,086	-6.54	4.44	-0.63	9.13
WEALTH - *family wealth*	395,979	-4.99	3.32	-0.80	9.87
CULTPOSS - *cultural possessions*	391,051	-1.93	1.47	-0.08	7.26
HEDRES - *home educational resources*	394,979	-4.84	1.65	-0.49	8.54
ISCEDL - *highest educational level of parent*	398,747	2.0	3.0	2.65	3.58
ST15Q01- *number books in the home*	390,779	1.0	6.0	2.94	10.66

Table 7 shows the range, mean and standard deviation for all the student level variables referenced thus far. Indexed variables with mean zero, determined from the OECD countries only, (i.e., ESCS, HOMEPOSS, WEALTH, CULTPOSS and HENDRESS) all appear to distribute normally about the mean. As suggested by Willms and Smith (2005), final student weights were used to calculate these values. Appendix B and C present detailed data for all countries; there are some violation to the normal distribution of these student level variables according to the values of skewness and kurtosis. Some variables are observed to be outside two standard errors of either shewness or kurtoisis (e.g., science self-efficacy for Israel); however, as the standard errors are much narrower here due to the large sample sizes in PISA analysis will progress without efforts to transform data to account for these violations. Similarly, normality assumptions can be relaxed when the sample size exceeds 50 (Newton & Rudestam, 1999).

Immigration background. The index of immigrant background was derived from students' responses to questions about whether or not they, their mother and father were born in the country of the assessment or in another country. The response categories were then grouped into: i) *native students* – those born in the country of the assessment with at least one parent also

born in the country; ii) *second generation students* – those born in the country of the assessment but whose parents were born in another country; and iii) *first generation students* – those born outside the country of assessment and whose parents were also born in another country. For the multilevel analysis, first and second generation students were grouped into a "students with an immigrant background". This variable can be referenced in both descriptive tables and histograms in Appendix B and C.

Science self-efficacy. The index of science self-efficacy was derived from students' beliefs in their ability to perform the following tasks: explain why earthquakes occur more frequently in some areas than others; recognize the science question that underlies a newspaper report on health; interpret the scientific information provided on the labeling of a food item; predict how changes to a environment will affect the survival of certain species; identify the science question associated with the disposal of garbage; describe the role of antibiotics in the treatment of disease; identify the better of two explanations for the formation of acid rain; discuss how new evidence can lead you to change our understanding about the possibility of life on Mars. These were initially measured on a 4 point likert scale of: SA-strongly agree, A-agree, D-disagree, and SD-strongly disagree. All items were inverted for IRT scaling and positive values on this index indicate higher levels of self efficacy in science. The descriptive statistics and histograms of science self-efficacy for all countries are shown in Appendix B and C and Table 8, and show that science self-efficacy is roughly normally distributed for all countries.

Science self-concept. The index of self-concept in science was derived from students' level of agreement with the following statements: I can usually give good answers to test questions on school science topics; when I am being taught school science; I can understand the concepts very well I learn school science topics quickly; I can easily understand new ideas in

school science; learning advanced school science topics would be easy for me; school science topics are easy for me. These were initially measured on a 4 point likert scale of: 1 – I could do this easily; 2 – I could do this with a bit of effort; 3 – I would struggle to do this on my own; and, 4 – I couldn't do this. The items were inverted for IRT scaling and positive values on this index indicate higher levels of self-concept in science. The descriptive statistics and histograms of science self-concept for all countries are shown in Appendix B and C, and show that science self-concept is roughly normally distributed for all countries. The overall descriptive statistics for science self-efficacy and self-concept are presented in Table 8.

Table 8

Descriptive Statistics of Science Self-efficacy and Self-concept for All Countries in PISA 2006

Variable	Min	Max	Mean	SD	*N*
Science self-efficacy	-3.78	3.22	-0.06	7.94	393,771
Science self-concept	-2.36	2.24	0.14	7.35	368,405

Table 8 shows the range, mean and standard deviation for the *science self-beliefs* variables of science self-efficacy and science self-concept. Detailed presentation of these variables for all countries that participated in PISA 2006 appears in Appendix B and C.

School-Level Variables

Proportion of immigrant students enrolled at school. I created country level measures of the proportion of native students (PROIMM) by aggregating the dummy coded student level immigrant status (i.e., 0-native and 1-non-native (a combination of second generation – those born in the country of assessment but whose parents are foreign born and first generation students - those foreign born whose parents are foreign born)).

School-level ESCS. In this case, the school-level variable School ESCS is the aggregated student-level variables for each school (SCHESCS).

Table 9

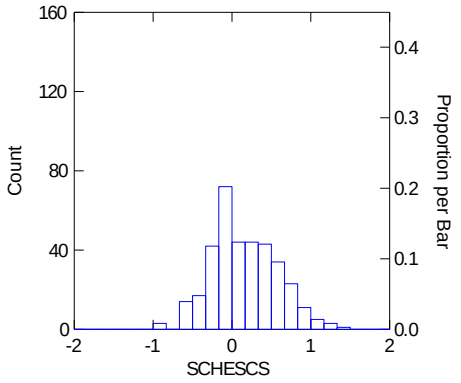
Descriptive Statistics of School-Level Variables for All Countries Involved in the Multilevel Models

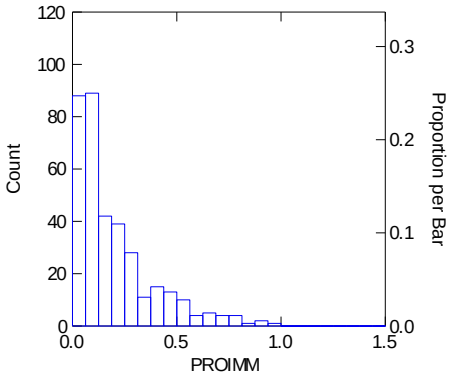
PROIMM	*N*	Min	Max	Mean	SD
Australia	356	0.00	0.949	0.192	0.193
Canada	896	0.00	1.00	0.127	0.205
Germany	226	0.00	0.812	0.156	0.179
New Zealand	170	0.00	1.00	0.199	0.187
Spain	686	0.00	1.00	0.053	0.102
The United States	166	0.00	0.897	0.161	0.215
SCHESCS	*N*	Min	Max	Mean	SD
Australia	356	-0.993	1.366	0.159	0.410
Canada	896	-1.518	1.564	0.261	0.431
Germany	226	-1.096	1.381	0.252	0.516
New Zealand	170	-1.015	1.102	0.070	0.389
Spain	686	-1.570	1.568	-0.198	0.553
The United States	166	-1.11	1.425	0.122	0.487

Table 9 shows the mean, range and standard deviation for the two s*chool level variables* used in the multilevel models for this study. These are both aggregates of PISA variables ESCS and the recoded immigrant status collected at the student level. Detailed presentation of these variables for all countries that participated in PISA 2006 appears in Appendix B and C. For the variable school level ESCS (SCHESCS), there are no obvious violation to the normal distribution of these variables according to the values of skewness and kurtosis. This is further emphasized in the histograms in Figure 1 below. Results for the proportion of immigrant students at the school level (PROIMM) are positively skewed for all six nations studied here; however, multilevel models such as those used in this study are robust to such deviations (Snijders & Bosker, 1999). Additionally, the population from which this variable is draw is not normally

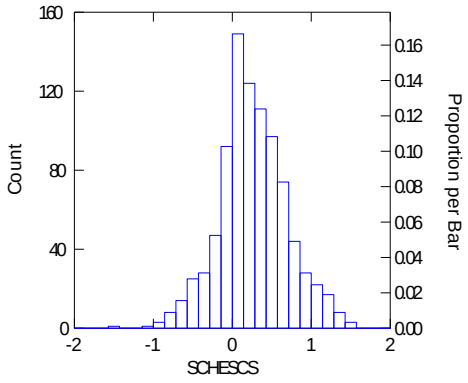
distributed.

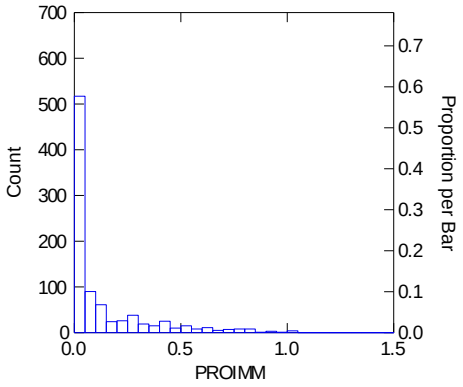
Australia



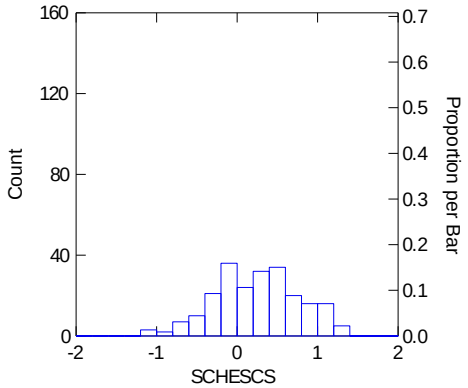


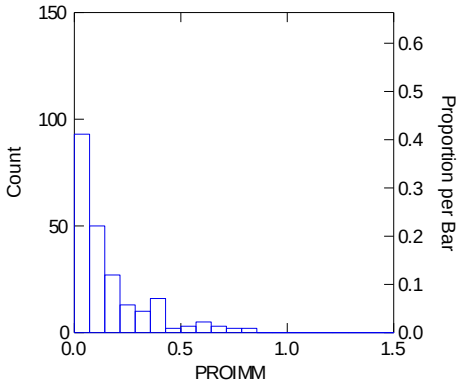
Canada





Germany





New Zealand

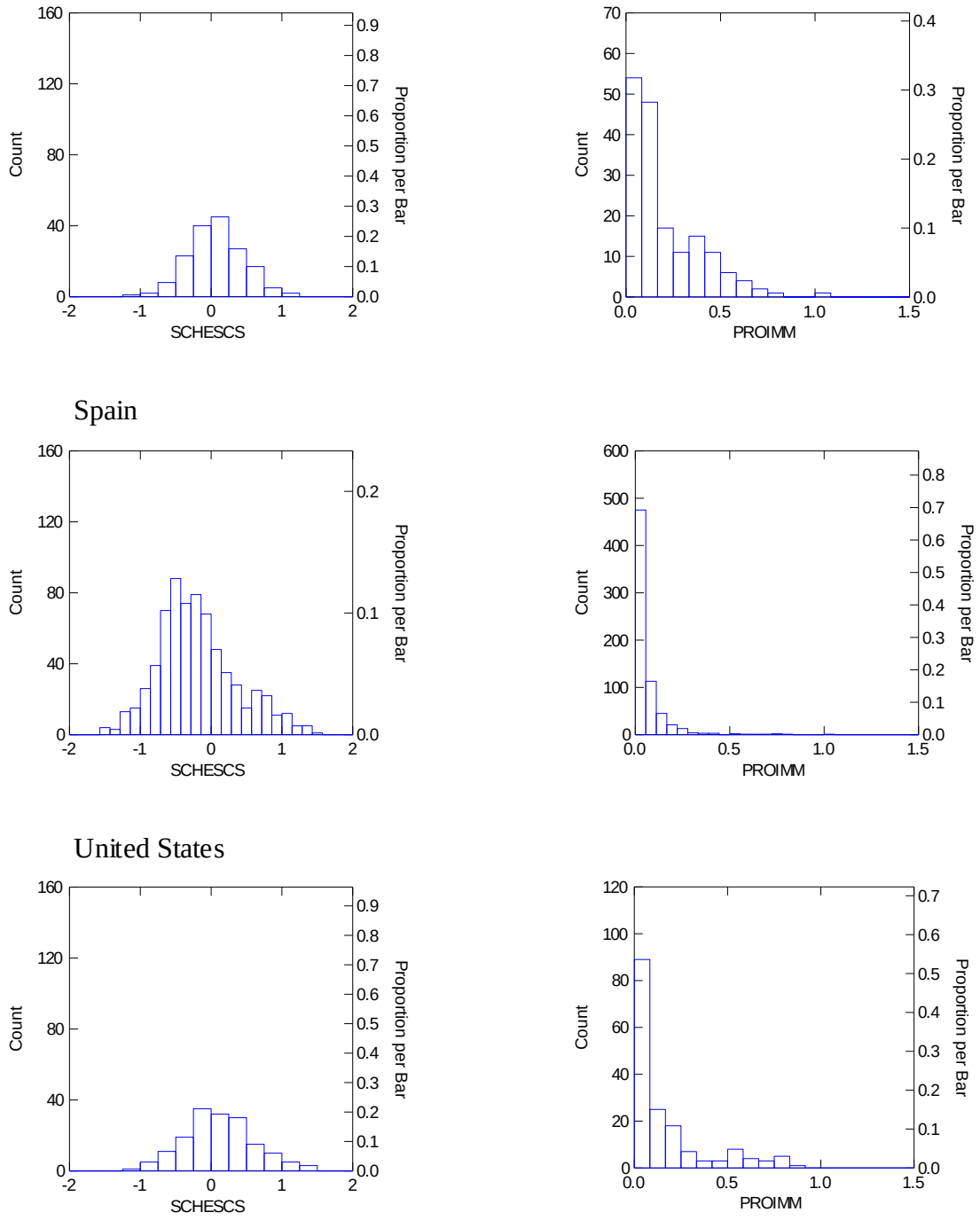


Figure 1. Histograms of school-level variables for all countries involved in the multilevel models.

Achievement Scores

Because PISA does not use simple random sampling, sample design weights were

employed to calculate most statistics. I measured student academic achievement by using mathematics, reading and science scores from the subject tests administered in the PISA 2006. Additionally, instead of one score for each student PISA provides a distribution of scores called plausible values that represent a random sample of what a student could have scored given the measurement error of the test. PISA provided 5 plausible values for each student and when using these for point estimation as well as test scores. Willms and Smith (2005) advise the use of averaged plausible values, and the combination of averaged sampling variance and imputation variance for calculating standard error. The descriptive and inferential data analysis for this paper was generated using SAS Version 9.1 (SAS Inc., Cary, NC) for Windows which allowed for both replicate weighting and the use of plausible values. When the analysis included multilevel models, HLM 6.06 (SSI Inc., Lincolnwood, IL) was used to deal with both plausible values and final student weights.

The descriptive statistics - maximum, minimum, mean, standard deviation, skewness, and kurtosis - for each of the five plausible values are very similar, and are detailed in Appendix C. Histograms of the five plausible values for each domain, for each country, are also given in Appendix E. For all countries and all domains, all five plausible values are roughly normally distributed, and satisfy statistical assumptions of skewness and kurtosis.

Science achievement. For each student who participated in the PISA 2006, there are five plausible values (PV1science – PV5science) in the datasets to indicate each student's general science ability achievement score. Scaling of the scores resulted in a mean of 500 points, and a standard deviation of 100 points for all OECD countries. The histograms of the general science ability scores for all countries involved in the multilevel models are shown in Appendix E.

Mathematics achievement. Similarly, there are also five plausible values (PV1math –

PV5math) for each student that participated in PISA 2006 in the datasets to indicate each student's mathematics literacy achievement score. Scaling of the scores resulted in a mean of 500 points, and a standard deviation of 100 points. The histograms of the science scores for all countries are presented in Appendix E, and show no violations of normal distribution, skewness or kurtosis.

Reading achievement. For each student who participated in the PISA 2006, there are five plausible values (PV1read – PV5read) in the datasets (notably the United States was absent from this measure in the data set; this is also evident for the histograms for plausible values in reading literacy in Appendix E as well as in the description of multilevel models later in this section) to indicate each student's reading literacy achievement score. Scaling of the scores resulted in a mean of 500 points, and a standard deviation of 100 points. The histograms of the reading literacy scores for all countries are shown in Appendix E. The maximum, minimum, mean, standard deviation, skewness, and kurtosis of reading literacy scores for all countries are presented in Appendix E.

Table 10

Mean Achievement Scores for All Domains and All Countries Involved in the Multilevel Models

Country	Science	Mathematics	Reading
Australia	524.63* (2.85)**	510.99 (2.68)	517.83 (2.74)
Canada	531.90 (2.35)	524.58 (2.58)	524.60 (2.12)
Germany	507.17 (5.51)	481.75 (7.10)	495.64 (5.63)
New Zealand	525.86 (4.01)	516.64 (4.20)	517.93 (3.44)

Spain	486.64 (2.82)	459.43 (2.91)	478.43 (2.70)
United States	489.66 (5.28)	473.85 (4.79)	Not reported

* Mean scores are from the *null models* and so have been adjusted for missing values. ** Standard errors are indicated in parentheses.

Table 10 shows the results of the null models for the six nations included in the multilevel analysis. HLM 6.06 was used to determine these estimates. There is consistency demonstrated in this data set both across columns (with countries scoring highest in science and consistently declining for reading and math) and down rows (with Canada scoring the highest in all three domains and Spain and the United States the lowest of the group). There is no obvious violation to the normal distributions of all the five plausible values of math scores according to the corresponding skewness and kurtosis (see Appendix E). Correlations across the country level for scientific, mathematics and reading literacy for PISA 2006 (as well as 2000 and 2003) can be referenced in Appendix J.

Summary of Descriptive Statistics

The samples of all students and nations in the PISA 2006 are representative of the population who are still at school and aged between 15 years 3 months and 16 years 2 months at the time of assessment, regardless of the grade, institutions, and full-time or part-time education. All nations consist of approximately equal numbers of boys and girls. All the variables at the student level and the school level are roughly normally distributed. Looking a little more closely at the counties involved in the multi-level analysis; Australia, Canada and New Zealand outperformed Germany, Spain and the United States on the mathematics, reading and science assessment. Additionally, science self-concept was below average for Australia and New Zealand when all other counties recorded it as positive and science self-efficacy was below average only for New Zealand and Spain. All nations recorded mean ESCS as slightly above

average (except Spain which was below average) and immigrant status was uniformly reported close to one (i.e., the vast majority of students are native (>.9)).

Science Literacy and Science Self-efficacy or Science Self-concept

Mean values with standard errors for scientific literacy, science self-efficacy and science self-concept by country are provided in dot charts below (see Figures 2, 3, and 4). Most country values appear to fall close to the OECD mean values of 500 (SD=100) for scientific literacy and mean values of 0 (SD=1) for science self-concept and science self-efficacy.

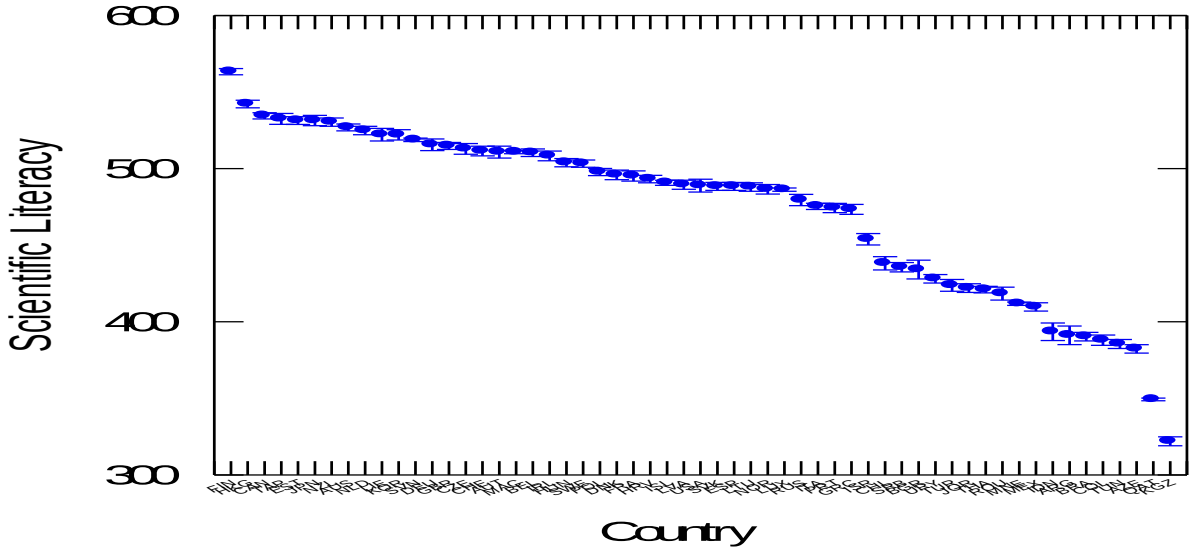


Figure 2. Dot charts of descending means with standard errors for scientific literacy for all nations in PISA 2006 (*n* = 57).

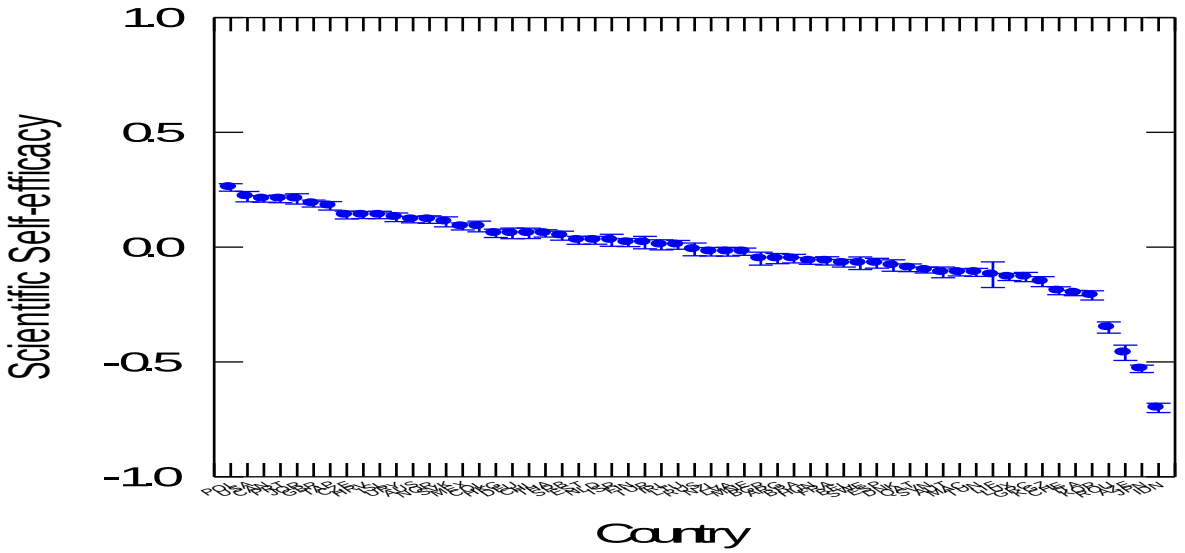


Figure 3. Dot charts of descending means with standard errors for scientific self-efficacy for all nations in PISA 2006 (*n* = 57).

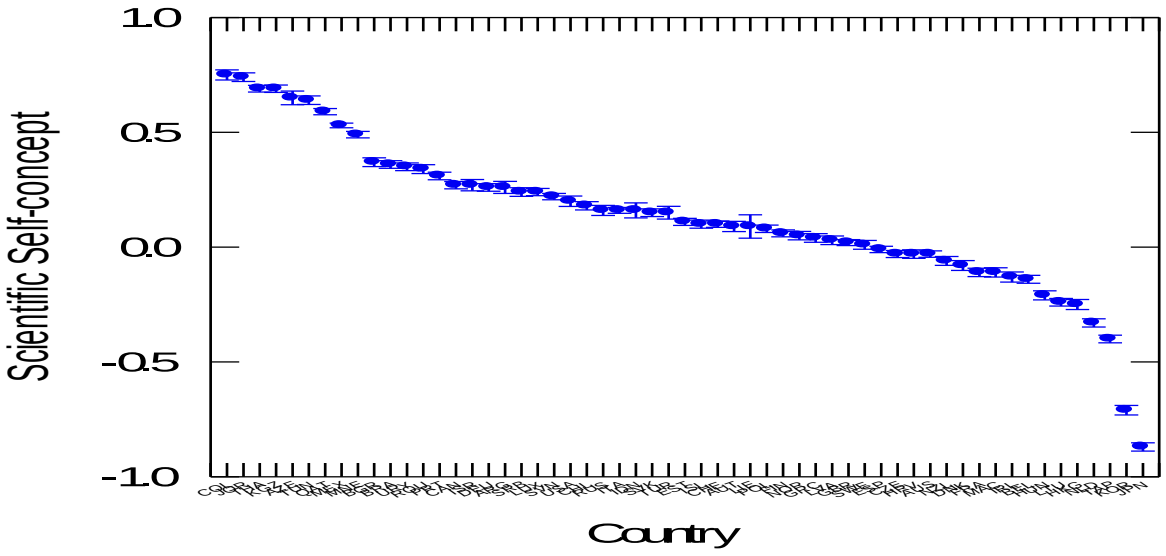


Figure 4. Dot charts of descending means with standard errors for scientific self-concept for all nations in PISA 2006 (n = 57).

Science literacy achievement and how it is related to science self-efficacy and science self-concept, based on the results of PISA 2006, are presented in Tables 10 and 11. Means and standard errors for either science self-efficacy (Table 11) or science self-concept (Table 12) and science literacy by country and internationally are presented. Within-country correlations between science self-efficacy and science achievement and science self-concept and science achievement are also presented in Tables 10 and 11, respectively. As the analysis was done in SAS, to determine if the correlation coefficients are significantly different from zero (H_0), I built confidence intervals around the coefficients (e.g., for Argentina and science self-efficacy, the coefficient can be computed as a value of α equal to 0.05 [0.24-(1.96*0.02); 0.24+(1.96*0.02)] = 0.20;0.28. As the coefficient does not include zero, it is significantly different from zero at this level of alpha.

Science Self-efficacy

At the country level, Poland was ranked first for science self-efficacy (M = 0.26, SE = 0

.016) and Indonesia was ranked last (M = -0.7, SE = 0 .020). The United States, Canada, Jordan and Portugal were included in the top five nations (M = 0.26 to 0.21) and Korea, Romania, Azerbaijan and Japan completed the list of bottom five nations (M = -0.21 to -0.53). I ranked the countries by average science self-efficacy and compared achievement for the upper half and the lower half (creating a median split). I found a statistically non-significant mean difference for science literacy, $t(54) = 1.413$, $p > .05$. Thus, the countries that ranked higher on science self-efficacy did not perform statistically better than those in the lower group. However, when the same analysis was performed on the top and bottom 19 nations (i.e., the top and bottom third), I found a statistically significant mean difference for scientific literacy, $t(36) = 14.9$, $p < .05$. In this analysis, the countries that ranked higher on science self-efficacy did perform statistically better than those in the lower third.

Internationally, at the student level, the overall correlation between student science self-efficacy and science literacy was positive and significant ($r = 0.33$, $p < .01$). I calculated this correlation coefficient by using within-country final sampling weights and the first plausible value for science (PV1). This would suggest that at the student level, students with higher science self-efficacy tend to have higher science achievement. Using the country level aggregates of science self-efficacy and science literacy, I calculated the country level correlation between science self-efficacy and science literacy (n = 57). This time, the relationship was positive but not statistically significant ($r = 0.23$, $p > .05$). For within-country analysis, I found a statistically significant positive correlation ($p < .05$) between science self-efficacy and science literacy for all 57 nations in PISA 2006. The magnitude of these statistically significant correlation coefficients ranged from a high of .49 for Australia to a low of .06 for Kyrgyzstan. These finding suggest that there is a positive within-country relationship between science self-efficacy and science literacy

as measured on PISA.

Table 11

Country-Level Means and Standard Errors for the Correlations Between Science Self-efficacy and Science Achievement, by Country-Level Self-efficacy

Country	Science self-efficacy	Standard error	Science literacy	Standard error	*r*
Argentina	-0.05	0.02	391.2	6.08	0.24***
Australia	0.12	0.01	526.9	2.26	0.49***
Austria	-0.11	0.02	510.8	3.92	0.44***
Azerbaijan	-0.46	0.03	382.3	2.75	0.15***
Belgium	-0.07	0.02	510.4	2.48	0.40***
Bulgaria	-0.05	0.03	434.1	6.11	0.31***
Brazil	-0.05	0.02	390.3	2.79	0.29***
Canada	0.21	0.01	534.5	2.03	0.44***
Switzerland	-0.19	0.02	511.5	3.16	0.42***
Chile	0.06	0.02	438.2	4.32	0.30***
Columbia	0.09	0.02	388	3.37	0.23***
Czech Republic	0.14	0.02	512.9	3.48	0.35***
Germany	0.06	0.02	515.6	3.8	0.45***
Denmark	-0.08	0.03	495.9	3.11	0.46***
Spain	-0.07	0.02	488.4	2.57	0.41***
Estonia	0.03	0.01	531.4	2.52	0.43***
Finland	0.02	0.01	563.3	2.02	0.44***
France	-0.06	0.01	495.2	3.36	0.42***
United Kingdom	0.19	0.01	514.8	2.29	0.52***
Greece	-0.13	0.02	473.4	3.23	0.31***
Hong Kong - China	0.06	0.02	542.2	2.47	0.37***
Croatia	0.14	0.02	493.2	2.45	0.42***
Hungary	-0.06	0.01	503.9	2.68	0.31***
Indonesia	-0.7	0.02	393.5	5.73	0.14***
Ireland	0.01	0.02	508.3	3.19	0.45***
Iceland	0.14	0.02	490.8	1.64	0.46***
Israel	0.03	0.03	453.9	3.71	0.20***
Italy	-0.2	0.01	475.4	2.02	0.28***
Jordan	0.21	0.02	422	2.84	0.20***
Japan	-0.53	0.02	531.4	3.37	0.32***
Kyrgyzstan	-0.15	0.02	322	2.93	0.06***
Korea	-0.21	0.02	522.1	3.36	0.38***
Liechtenstein	-0.12	0.06	522.2	4.1	0.37***
Lithuania	0.01	0.02	488	2.76	0.34***
Luxembourg	-0.13	0.02	486.3	1.05	0.35***
Latvia	-0.02	0.02	489.5	2.97	0.34***

Macedonia	-0.11	0.02	510.8	1.06	0.32***
Mexico	0.09	0.02	409.7	2.71	0.23***
Montenegro	-0.02	0.02	411.8	1.06	0.37***
Netherlands	0.03	0.02	524.9	2.74	0.33***
Norway	0.12	0.02	486.5	3.11	0.37***
New Zealand	-0.02	0.02	530.4	2.69	0.52***
Poland	0.26	0.02	497.8	2.34	0.44***
Portugal	0.21	0.02	474.3	3.02	0.33***
Qatar	-0.09	0.02	349.3	0.86	0.18***
Romania	-0.35	0.02	418.4	4.2	0.27***
Russian Federation	-0.01	0.03	479.5	3.67	0.32***
Serbia	0.05	0.02	435.6	3.04	0.31***
Slovak Republic	0.11	0.02	488.4	2.59	0.31***
Slovenia	-0.1	0.01	518.8	1.11	0.37***
Sweden	-0.07	0.02	503.3	2.37	0.42***
Chinese Taipei	0.18	0.02	532.5	3.57	0.38***
Thailand	0.06	0.02	421	2.14	0.17***
Tunisia	-0.11	0.02	385.5	2.96	0.19***
Turkey	0.02	0.03	423.8	3.84	0.35***
Uruguay	0.13	0.02	428.1	2.75	0.29***
United States	0.22	0.02	488.9	4.22	0.39***
Student Level	-0.06	0.01	461.4	1.26	0.33**
Country Level	-0.23	0.02	473.2	7.23	0.23

*p < .05. **p < .01. ***p < .001.

Science Self-concept

Similar to the analysis for science self-efficacy, science self-concept and science literacy were also analyzed at the student and country level (Table 12). At the country level, Columbia was ranked first for science self-concept (M = 0.75, SE = 0 .022) and Japan was ranked last (M = -0.87, SE = 0 .018). Jordan, Thailand, Kyrgyzstan and Azerbaijan were included in the top five nations (M = 0.26 to 0.21) and Hong Kong – China, the Netherlands, Chinese Taipei and Korea completed the list of bottom five nations (M = -0.24 to -0.71). As a geographical effect was anticipated *a priori*, of note here is that four of the five nations that ranked lowest on self-concept were Asian. I again ranked the countries by average science self-concept and compared achievement for the upper half and the lower half (creating a median split). This time, I found a statistically significant mean difference for science literacy, $t(54) = -7.22$, $p < .05$. The difference shows that, on average and as a group, the countries that ranked higher on science self-concept

performed less well on science achievement than the group of countries with lower science self-concept.

Internationally, at the student level, the overall correlation between student science self-concept and science literacy was positive and significant ($r = 0.22$, $p < .001$). I calculated this correlation coefficient by using within-country final sampling weights and the first plausible value for science (PV1). This finding suggests that at the student level, students with higher science self-concept tend to have higher achievement. Using country level aggregates of science self-concept and science literacy, I calculated the country level correlation between science self-concept and science literacy (n = 57). This time, the relationship was negative and statistically significant ($r = -0.74$, $p < .001$). This is a noteworthy finding and would suggest that, on average, countries with higher science self-concept tend to achieve lower on scientific literacy (and vice versa).

For within-country analysis, I found a statistically significant positive correlation ($p < .05$) between science self-concept and science literacy for 48 of the 57 nations in PISA 2006 (exceptions being Argentina, Azerbaijan, Brazil, Columbia, Montenegro, Romania and Thailand). Indonesia and Kyrgyzstan were statistically significant but negatively correlated with scientific literacy. The magnitude of these statistically significant correlation coefficients ranged from a high of 0.46 for Iceland to a low of 0.06 for Mexico. These finding suggest that there is a positive within-country relationship between science self-concept and science literacy as measured on PISA.

Table 12

Country-Level Means and Standard Errors for the Correlations Between Science Self-concept and Science Achievement, by Country-Level Self-concept

Country	Science self-concept	Standard error	Science literacy	Standard error	*r*
Argentina	0.26	0.03	391.2	6.08	0.04
Australia	-0.03	0.01	526.9	2.26	0.43***
Austria	0.09	0.02	510.8	3.92	0.26***
Azerbaijan	0.65	0.03	382.3	2.75	0.02
Belgium	-0.14	0.02	510.4	2.48	0.26***
Bulgaria	0.37	0.02	434.1	6.11	0.07***
Brazil	0.36	0.02	390.3	2.79	0.02
Canada	0.27	0.02	534.5	2.03	0.40***
Switzerland	0.1	0.01	511.5	3.16	0.30**
Chile	0.18	0.02	438.2	4.32	0.19***
Columbia	0.75	0.02	388	3.37	0.03
Czech Republic	-0.03	0.02	512.9	3.48	0.10**
Germany	0.26	0.02	515.6	3.8	0.26***
Denmark	-0.08	0.02	495.9	3.11	0.35***
Spain	-0.01	0.01	488.4	2.57	0.31***
Estonia	0.11	0.02	531.4	2.52	0.27***
Finland	0.06	0.02	563.3	2.02	0.41***
France	-0.11	0.02	495.2	3.36	0.28***
United Kingdom	0.02	0.01	514.8	2.29	0.33***
Greece	0.04	0.02	473.4	3.23	0.17***
Hong Kong - China	-0.25	0.02	542.2	2.47	0.24***
Croatia	-0.03	0.02	493.2	2.45	0.14***
Hungary	-0.21	0.02	503.9	2.68	0.11***
Indonesia	0.16	0.03	393.5	5.73	-0.26***
Ireland	-0.13	0.02	508.3	3.19	0.39***
Iceland	0.1	0.02	490.8	1.64	0.46***
Israel	0.27	0.03	453.9	3.71	0.26***
Italy	0.16	0.01	475.4	2.02	0.14***
Jordan	0.74	0.02	422	2.84	0.2***
Japan	-0.87	0.02	531.4	3.37	0.25***
Kyrgyzstan	0.69	0.02	322	2.93	-0.23***
Korea	-0.71	0.02	522.1	3.36	0.36***
Liechtenstein	0.09	0.05	522.2	4.1	0.22***
Lithuania	-0.24	0.02	488	2.76	0.2***
Luxembourg	0.24	0.02	486.3	1.05	0.26***
Latvia	0.03	0.02	489.5	2.97	0.12***
Macedonia	-0.11	0.02	510.8	1.06	0.15***
Mexico	0.53	0.01	409.7	2.71	0.06**
Montenegro	0.49	0.01	411.8	1.06	0.02
Netherlands	-0.33	0.02	524.9	2.74	0.25***
Norway	0.05	0.02	486.5	3.11	0.37***
New Zealand	-0.06	0.02	530.4	2.69	0.37***
Poland	0.08	0.02	497.8	2.34	0.2***
Portugal	0.31	0.02	474.3	3.02	0.23***
Qatar	0.59	0.01	349.3	0.86	0.1***

Romania	0.34	0.02	418.4	4.2	0.02
Russian Federation	0.16	0.02	479.5	3.67	0.11***
Serbia	0.24	0.02	435.6	3.04	0.07***
Slovak Republic	0.15	0.02	488.4	2.59	0.16***
Slovenia	0.22	0.01	518.8	1.11	0.09***
Sweden	0.01	0.02	503.3	2.37	0.43***
Chinese Taipei	-0.4	0.02	532.5	3.57	0.14***
Thailand	0.69	0.02	421	2.14	-0.04
Tunisia	0.64	0.02	385.5	2.96	0.08***
Turkey	0.15	0.03	423.8	3.84	0.13***
Uruguay	0.35	0.02	428.1	2.75	0.12***
United States	0.2	0.02	488.9	4.22	0.28***
Student Level	0.14	0.01	461.4	1.26	0.22***
Country Level	0.13	0.42	473.2	7.23	-0.74***

*p < .05. **p < .01. ***p < .001.

Economic, Cultural, and Social Capital

Multiple regression equations for science literacy predicted by the indicators of economic, cultural and social capital – as well as the composite ESCS – are listed below in Tables 13 thru 17. These models were created using the macros made available by the OECD to facilitate SAS analyze of the PISA data sets. These macros allowed for the computation of the intercept term, regression coefficients and the R^2 value (multiple coefficient of determination) with appropriately calculated standard errors (i.e., they allowed for the multiple imputations of 5 plausible values and 81 replicate weights) (OECD, 2009a).

Table 13

Correlations Among the Constructs of Socio-economic Status for All Student-Level Data (n = 368,425)

	1	2	3	4	5	6	7
1.Cultural possessions (CULTPOSS)	1.000*						
2. Books in the home (BOOKS)	0.423*	1.000*					
3.Classification of education (ISCEDL)	0.040*	0.102*	1.000*				
4. Home education resources (HEDRES)	0.353*	0.411*	0.080*	1.000*			
5. Highest parental occupation (HISEI)	0.253*	0.386*	0.165*	0.341*	1.000*		
6. Family wealth (WEALTH)	0.220*	0.404*	0.168*	0.571*	0.422*	1.000*	
7. Index of home possession (HOMEPOS)	0.518*	0.593*	0.131*	0.754*	0.469*	0.888*	1.000*
8. ESCS (ESCS)	0.419*	0.563*	0.174*	0.607*	0.808*	0.739*	0.814*

*Correlations are significant at the .05 level.

The correlations between the constructs of socioeconomic status as defined by PISA (Table 13) for all nations were calculated using SYSTAT 11 (Systat Software Inc., Chicago, IL). Significant correlations are indicated at a $p < .05$ for all countries after a Bonferroni correction. With the exception of the International Standard Classification of Education (ISCEDL), these constructs are moderately, positively and in some cases highly correlated (e.g., Index of Home Possessions (HOMEPOSS) and ESCS; Index of Home Possessions (HOMEPOSS) and Family Wealth (WEALTH)). However, the only constructs that are both highly correlated and will be used in the same regression equation are the Index of Home Possessions (HOMEPOSS) and Family Wealth (WEALTH). This does present a potential problem with co-linearity and the

potential uncertainty of the standard errors and regression coefficients.

As has been noted previously, the histograms and descriptive details by country are provided in Appendix B and C and requirement for normalcy are generally met. Additionally, scatterplot matrices for select variables used in the regression as well as residual plots from those same regression equations are presented in Appendix F and G. From these, linear relations among the variables are supported as well as the absence of heteroscedasticity. Because of the nature of the correlations, simultaneous entry multiple regression analysis was selected to determine how much of the variance in scientific literacy can be explained (not to imply cause and effect) by a combination of the constructs which make up the PISA definition of socioeconomic status.

Results for these multiple regressions are difficult to interpret convincingly because the amount of variance explained by an independent variable in the model is highly dependent upon the other variables already in the model (Turmo, 2004). To account for this overlapping variance among variables and the co-linearity problem mentioned above, partial (the removal of the overlapping variance created by the presence of other independent variables from both the dependent and independent) and semi-partial (removal of overlapping variance from the independent variable only) correlations can be calculated (Newton & Rudestam, 1999). Some of these are provided below in the results; however, due to the nature of the PISA data set and limitation of the SAS macros, this was not done for all regression equations. Because of this, the focus for this analysis will be upon the multiple coefficients of determination produced for each country for each equation (see Tables 13 to 17). This R^2 value is defined as the total variance explained by the combined independent variables in the model (Howell, 2004).

The regression models were created by entering all of the variables of interest into SAS using the OECD provided macros which weighted results to provide more accurate estimates of

parameters and their errors. Any variables which were statistically non-significant are indicated in the output. To determine if the unstandardized regression coefficients are significantly different from zero, I built confidence intervals around the estimates for the regression coefficients (i.e., for Argentina and cultural possession coefficient can be computed as a value of α equal to 0.05 [5.31-(1.96*3.07); 5.31+(1.96*3.07)] = -0.71;11.33]. As the regression coefficient in this case includes zero, it is not significantly different from zero and this is indicated in the equation as void of any asterisk (i.e., cultural possessions do not significantly predict and account for the variance in science achievement for Argentina).

Table 14

Results of Regression Analysis by Country for Cultural Capital

$$Science = B_0 + B_1(CULTPOSS) + B_2(BOOKS) + B_3(ISCEDL) + r,$$

Country	Intercept	Cultural possessions at home	Books in the home	International Standard Classification of Education	R^2
Argentina	308.1	5.31	22.05***	9.79***	0.18***
Australia	405.59	5.45***	19.74***	11.36***	0.15***
Austria	390.86	5.29***	29.33***	5.07**	0.23***
Azerbaijan	332.88	1.30	7.69***	6.84***	0.07***
Belgium	398.82	14.24***	16.33***	14.56***	0.20***
Bulgaria	297.13	21.34***	22.17***	15.08***	0.27***
Brazil	329.69	-1.43	15.38***	9.42***	0.11***
Canada	424.96	4.1***	16.75***	10.49***	0.11***
Switzerland	387.39	1.54	26.28***	9.27***	0.21***
Chile	336.23	5.76***	19.18***	14.91***	0.22***
Columbia	328.3	-2.26	20.24***	5.34***	0.11***
Czech Republic	380.67	9.94***	25.8***	9.28***	0.19***
Germany	382.6	4.4***	26.88***	10.39***	0.24***
Denmark	388.12	10.83***	18.27***	10.65***	0.19***
Spain	393.1	10.71***	19.96***	7.23***	0.20***
Estonia	427.48	5.4***	19.51***	5.98***	0.13***
Finland	465.64	10.45***	15.37***	8.27***	0.12***
France	391.18	15.14***	22.94***	9.08***	0.26***
United Kingdom	410.98	5.05***	27.15***	4.63***	0.19***
Greece	366.47	5.83***	15.43***	13.55***	0.16***
Hong Kong - China	482.81	6.58**	16.88***	6.4***	0.10***

Croatia	419.8	11.6***	17.49***	7.76***	0.16***
Hungary	360.09	9.88***	19.11***	16.13***	0.28***
Indonesia	355.09	-2.15	6.57***	8.5***	0.07***
Ireland	402.66	8.91***	21.15***	8.48***	0.18***
Iceland	361.7	9.63***	18.95***	11.03***	0.14***
Israel	347.09	19.27***	11.66***	14.5***	0.12***
Italy	384.84	9.81***	19.62***	6.27***	0.14***
Jordan	363.74	6***	5.31***	13.17***	0.11***
Japan	418.56	13.97***	9.93***	17.68***	0.12***
Kyrgyzstan	261.04	8.93***	19.74***	4.36**	0.12***
Korea	433.31	14.99***	18.39***	4.43***	0.15***
Liechtenstein	413.13	12.32	15.76***	13.77***	0.21***
Lithuania	379.9	16.84***	16.22***	11.39***	0.18***
Luxembourg	367.46	8.06***	22.11***	10.05***	0.26***
Latvia	388.45	12***	15.49***	8.94***	0.12***
Macedonia	497.12	12.06***	4.53***	3.43***	0.04***
Mexico	364.33	4.42***	11.44***	8.58***	0.14***
Montenegro	356.86	18.95***	11.18***	3.79***	0.13***
Netherlands	414.6	4.79***	23.44***	7.51***	0.20***
Norway	389.82	12.51***	16.86***	6.67***	0.14***
New Zealand	396.52	4.04***	25.27***	11.03***	0.18***
Poland	375.29	7.03***	16.48***	17.72***	0.19***
Portugal	415.34	11.02***	15.76***	5.55***	0.17***
Qatar	315.85	5.83***	2.11**	7.1***	0.04***
Romania	330.45	13.27***	18.56***	5.66**	0.19***
Russian Federation	375.8	5.98***	15.11***	10.24***	0.09***
Serbia	371.22	16.27***	15.54***	4.86***	0.15***
Slovak Republic	322.72	6.03***	23.17***	20.2***	0.23***
Slovenia	397.14	14.68***	21.7***	13.02***	0.22***
Sweden	394.28	5.55**	22.96***	4.85***	0.16***
Chinese Taipei	436.25	18.11***	15.71***	12.1***	0.20***
Thailand	365.41	-0.33	12.88***	11.05***	0.14***
Tunisia	353.38	11.28***	11.98***	4.81***	0.09***
Turkey	364.56	9.30***	13.65***	9.74***	0.17***
Uruguay	350.63	9.91***	16.67***	9.88***	0.17***
United States	343.14	5.43***	25.18***	14.08***	0.22***

*p < .05. **p < .01. ***p < .001.

Table 13 shows the results for the series of multiple regression equations run for variables associated with cultural capital and scientific literacy from PISA 2006. This model consists of an index of cultural possessions in the home (CULTPOSS), an index of books in the home (BOOKS) and the International Standard Classification of Education (ISCEDL). The interpretation of the unstandardized regression coefficients is that they represent the amount of change in the dependent variable associated with a one unit change in the independent variable,

with all other independent variables held constant (Newton & Rudestam, 1999). However, as stated, the interpretation will focus on the multiple coefficients of determination (R^2) produced for each country

The results in Table 14 demonstrate a range across countries of the extent to which the variance in scientific literacy is explained by the variables which comprise cultural capital. The R^2 values ranges from a low of 0.04 in Macedonia to a high of 0.28 in Hungary (indicating that these variables account for 4% and 28% of the variance in science literacy in these countries respectively). Overall the R^2 value was 0.16 for all nations indicating that 16% of scientific literacy was explained by cultural capital. All countries had R^2 values that were significantly different from zero at $p<.05$.

Table 15

Results of Regression Analysis by Country for Social Capital

$$Science = B_0 + B_1(HEDRES) + B_2(HISEI) + r$$

Country	Intercept	Home educational resources	Highest parental occupation	R^2
Argentina	357.2	28.79***	1.3***	0.19***
Australia	442.16	17.75***	1.64***	0.11***
Austria	414.5	11.02***	1.91***	0.13***
Azerbaijan	379.76	9.19***	0.36***	0.07***
Belgium	409.99	19.53***	2.05***	0.18***
Bulgaria	366.72	29.79***	2***	0.24***
Brazil	367.73	24.34***	1.28***	0.21***
Canada	459.5	9.74***	1.47***	0.08***
Switzerland	408.89	8.07***	2.07***	0.13***
Chile	375.3	17.06***	1.85***	0.21***
Columbia	370.99	17.55***	0.82***	0.13***
Czech Republic	399.23	20.51***	2.33***	0.18***
Germany	415.92	16.32***	2.04***	0.16***
Denmark	420.1	7.04***	1.58***	0.10***
Spain	416.4	15.77***	1.57***	0.13***
Estonia	458.48	7.54***	1.49***	0.10***
Finland	508	3.51***	1.16***	0.06***
France	382.71	16.07***	2.29***	0.20***
United Kingdom	416.32	20.54***	2.1***	0.14***
Greece	419.79	26.58***	1.49***	0.18***

Hong Kong - China	499.12	14.62***	1.08***	0.05***
Croatia	417.98	16.73***	1.67***	0.14***
Hungary	422.87	20.77***	1.76***	0.19***
Indonesia	387.62	15.31***	0.77***	0.11***
Ireland	442.15	17.07***	1.45***	0.11***
Iceland	422.6	14.15***	1.23***	0.07***
Israel	375.91	24.86***	1.79***	0.10***
Italy	406.84	19.05***	1.41***	0.12***
Jordan	402.28	21.47***	1.03***	0.14***
Japan	492.85	12.14***	0.98***	0.04***
Kyrgyzstan	303.18	15.81***	0.92***	0.10***
Korea	482.61	22.36***	0.86***	0.07***
Liechtenstein	410.46	9.77**	2.18***	0.13***
Lithuania	432.05	25.61***	1.21***	0.17***
Luxembourg	369.84	9.19***	2.41***	0.19***
Latvia	434.88	15.55***	1.18***	0.11***
Macedonia	508.79	20.34***	0.27***	0.05***
Mexico	379.49	16.65***	1.06***	0.17***
Montenegro	364.16	12.38***	1.13***	0.11***
Netherlands	421.34	19.1***	2.04***	0.17***
Norway	403.58	13.95***	1.63***	0.10***
New Zealand	436.4	20.96***	1.97***	0.13***
Poland	421.09	15.23***	1.7***	0.13***
Portugal	396.06	17.23***	1.8***	0.18***
Qatar	327.74	23.38***	0.86***	0.08***
Romania	363.86	14.82***	1.51***	0.20***
Russian Federation	434.75	17.36***	1***	0.10***
Serbia	368.78	13.9***	1.46***	0.15***
Slovak Republic	412.54	21.31***	1.7***	0.20***
Slovenia	406.43	16.63***	2.2***	0.16***
Sweden	420.78	8.88***	1.71***	0.11***
Chinese Taipei	483.27	18.88***	1.3***	0.10***
Thailand	417.17	22.75***	0.98***	0.19***
Tunisia	380.78	19.17***	0.76***	0.15***
Turkey	390.65	17.37***	1.18***	0.17***
Uruguay	374.38	21.12***	1.47***	0.18***
United States	401.35	17.7***	1.89***	0.13***

*p < .05. **p < .01. ***p < .001.

Table 15 shows the results for the series of multiple regression equations run for variables associated with social capital and scientific literacy from PISA 2006. This model consists of an index of home educational resources (HEDRES), and highest parental occupation (HISEI). The results in Table 15 demonstrate a range across countries of the extent to which the variance in scientific literacy is explained by the variables which comprise social capital. The R^2 values

ranges from a low of 0.05 in Macedonia and Hong Kong – China to a high of 0.24 in Bulgaria (indicating that these variables account for 5% and 24% of the variance in science literacy in these countries respectively). Overall the R^2 value was 0.14 for all nations indicating that 14% of scientific literacy was explained by cultural capital. All countries had R^2 values that were significantly different from zero at $p<.05$.

Table 16

Results of Regression Analysis by Country for Economic Capital

$$Science = B_0 + B_1(WEALTH) + B_2(HOMEPOS) + r$$

Country	Intercept	Family wealth	Index of home possessions	R^2
Argentina	427.04	-16.67***	53.46***	0.17***
Australia	537.45	-57.17***	65.48***	0.10***
Austria	499.68	-49.17***	72.59***	0.14***
Azerbaijan	375.41	-15.37***	18.35***	0.04***
Belgium	511.4	-42.94***	74.75***	0.15***
Bulgaria	451.26	-59.06***	89.88***	0.23***
Brazil	445.89	15.25***	23.55***	0.17***
Canada	541.78	-41.04***	49.02***	0.06***
Switzerland	512.58	-53.62***	71.75***	0.11***
Chile	464.08	-17.09***	49***	0.18***
Columbia	414.54	-4.22***	26.56***	0.11***
Czech Republic	488.63	-67.08***	87.41***	0.15***
Germany	505.26	-52.11***	75.15***	0.15***
Denmark	501.13	-26.42***	48.21***	0.11***
Spain	472.33	-60.65***	74.94***	0.14***
Estonia	514.3	-47.71***	58.85***	0.09***
Finland	571.95	-38.81***	48.21***	0.07***
France	478.4	-77.12***	102.52***	0.21***
United Kingdom	528.12	-48.6***	69.03***	0.13***
Greece	490.24	-56.53***	74.73***	0.13***
Hong Kong - China	545.85	-38.54***	49.89***	0.08***
Croatia	488.91	-54.16***	68.36***	0.13***
Hungary	483.06	-69.73***	85.31***	0.21***
Indonesia	435.43	7.38***	11.3***	0.09***
Ireland	516.42	-47.87***	63.04***	0.12***
Iceland	505.21	-72.45***	63.17***	0.11***
Israel	445.22	-58.96***	78.75***	0.12***
Italy	455.81	-58.91***	72.69***	0.12***
Jordan	448.19	-17.76***	36.75***	0.08***
Japan	558.32	-60.79***	68.69***	0.07***

Kyrgyzstan	317.8	-30.17***	42.23***	0.09***
Korea	520.54	-47.36***	63***	0.12***
Liechtenstein	516.46	-39.3***	61.35***	0.11***
Lithuania	470.84	-56.73***	75.75***	0.17***
Luxembourg	478.1	-37.6***	61.29***	0.14***
Latvia	464.88	-46.27***	63.28***	0.11***
Macedonia	522.57	-37.1***	44.04***	0.06***
Mexico	436.86	-2.41***	26.29***	0.13***
Montenegro	390.29	-67.59***	66.44***	0.14***
Netherlands	539.04	-46.19***	69.34***	0.15***
Norway	499.39	-55.39***	58.33***	0.11***
New Zealand	534.68	-32.87***	61.28***	0.12***
Poland	468.96	-53.89***	65.98***	0.12***
Portugal	465.61	-35.59***	57.41***	0.16***
Qatar	369.53	-45.44***	39.1***	0.06***
Romania	402.42	-51.1***	62.79***	0.17***
Russian Federation	447.08	-50.01***	59.19***	0.08***
Serbia	422.87	-54.87***	67.79***	0.14***
Slovak Republic	465.67	-59.75***	77.95***	0.17***
Slovenia	501.18	-69.28***	82.67***	0.16***
Sweden	523.47	-43.72***	52.76***	0.08***
Chinese Taipei	546.93	-77.20***	80.84***	0.16***
Thailand	459.08	-8.4***	35.19***	0.14***
Tunisia	406.15	-22.59***	37.35***	0.10***
Turkey	432.92	-28.79***	47.59***	0.16***
Uruguay	436.08	-33.75***	60.31***	0.15***
United States	501.53	-33.91***	61.53***	0.14***

*p < .05. **p < .01. ***p < .001.

Table 16 shows the results for the series of multiple regression equations run for variables associated with economic capital and scientific literacy from PISA 2006. This model consists of an index of wealth in the home (WEALTH), and home possessions (HOMEPOSS). The results in Table 17 demonstrate a range across countries of the extent to which the variance in scientific literacy is explained by the variables which comprise social capital. The R^2 values ranges from a low of 0.06 in Canada and Qatar to a high of 0.23 in Bulgaria (indicating that these variables account for 6% and 23% of the variance in science literacy in these countries respectively). Overall the mean R^2 value was 0.12 for all nations indicating that 12% of scientific literacy was explained by cultural capital; a smaller range and smaller reduction in variance. All countries had R^2 values that were significantly different from zero at $p<.05$.

Additionally, as mentioned previously, this equation was at risk for a co-linearity problem. As an inquiry extension, Germany was regressed for economic capital using (SPSS Inc., Chicago: SPSS Inc.) to determine the partial and semi-partial correlation coefficients. The output for Germany in Table 16 was 505.26 for the intercept, -52.11 for family wealth slope, 75.15 for home possessions slope and an R^2 value of 0.15 (all terms being highly-significant). When analyzed with SPSS and using only the first plausible value for science, results were 505.1 for the intercept, -53.24 for family wealth slope, 75.89 for home possessions slope and an R^2 value of 0.15 (again, all terms significant at $p<.000$). With the exception of standard error values, this was consistent with the SAS results.

The zero order correlations for wealth and home possessions were 0.17 and 0.32 with the dependent variable and 0.86 with each other. The semi-partial correlations (i.e., the total sum of squares around the dependent variable) were -0.22 and 0.35 for wealth and home possessions respectively and the partial correlations (removal of overlapping variance from both the dependent and independent) were -0.23 and 0.36 respectively. Because the semi-partial correlation is a more consistent measure as it maintains the total sum of squares around the dependent variable, the semi-partial represents the unique variability contributing to the regression equation (Newton & Rudestam, 1999). In this equation, the semi-partial represents the reduction in R^2 if the variable was removed; sizable for home possessions and moderate for wealth.

When the regression was rerun with each of the independent variables on their own, using only the first plausible value for science (PV1SCIE), results were 506.0 for the intercept, 35.48 for home possessions slope and an R^2 value of 0.10 (again, all terms significant at $p<.000$). Run again with only wealth, results were 512.9 for the intercept, 20.69 for the wealth slope and

an R^2 value of 0.03 (all terms significant at $p<.000$). For ease of interpretation and a more accurate determine how much of the variance in scientific literacy can be explained by the constructs of economic capital, this analysis was rerun with the variables on their own. Results can be found in Table 17.

Table 17

Results of Regression Analysis by Country for Economic Capital – Rerun for WEALTH and HOMEPOS in Separate Equations

Country	Intercept	Family wealth	R^2	Intercept	Index of home possessions	R^2
Argentina	444.19	39.13***	0.13***	434.57	39.74***	0.17***
Australia	525.55	4.75***	0	522.67	24.82***	0.04***
Austria	508.12	18.28***	0.02***	501.43	36***	0.10***
Azerbaijan	388.78	3.1***	0	391.93	7.18***	0.02
Belgium	506.62	22.94***	0.03***	506.92	40.83***	0.12***
Bulgaria	455.09	30.06***	0.07***	461.83	43.63***	0.18***
Brazil	448.83	38.34***	0.16***	440.04	36.29***	0.17***
Canada	534.98	7.62***	0	535.85	19.64***	0.03***
Switzerland	510.72	9.32***	0	509.89	30.19***	0.06***
Chile	474.78	35***	0.13***	469.55	35.12***	0.17***
Columbia	430.69	24.67***	0.09***	417.55	23.23***	0.11***
Czech Republic	521.47	19.38***	0.02	514.81	34.8***	0.09***
Germany	512.41	21.41***	0.03***	505.65	36.09***	0.10***
Denmark	488.9	8.13***	0.01***	485.18	28.52***	0.08***
Spain	490.39	12.7***	0.01***	485.37	28.93	0.07***
Estonia	535.13	8.92***	0.01***	532.15	19.57***	0.04***
Finland	562.31	2.86	0	560.64	19.62***	0.03***
France	502.18	25.86***	0.03***	496.29	44.72***	0.13***
United Kingdom	510.51	12.89***	0.01***	512.77	33.52***	0.08***
Greece	476.78	11.08***	0.01***	486.09	28.56***	0.07***
Hong Kong - China	547.43	12.33***	0.01	550.9	21.8***	0.05***
Croatia	499.29	14.02***	0.02***	500.59	26.5***	0.08***
Hungary	510.66	18.79***	0.03***	505.22	31.47***	0.12***
Indonesia	435.7	15.9***	0.08***	429.48	18.2***	0.09***
Ireland	507.94	12.99***	0.01***	510.36	30.79***	0.08***
Iceland	504.81	-13.19***	0.01***	484.03	8.53***	0.01***
Israel	459.12	16.58***	0.02	455.76	28.5***	0.07***
Italy	477.64	16.73***	0.02***	470.49	29.39***	0.07***
Jordan	449.61	19.26***	0.05***	453.11	22.2***	0.08***
Japan	532.35	7.98***	0	543	23.57***	0.03***
Kyrgyzstan	344.23	9.94***	0.01***	349.66	18.68***	0.06***

Korea	527.07	17.05***	0.02	527.52	28.34***	0.08***
Liechtenstein	516.49	16.1***	0.02	511.57	31.92***	0.08***
Lithuania	501.58	23.91***	0.04***	494.57	33.18***	0.12***
Luxembourg	478.91	22.99***	0.04***	474.76	34.8***	0.11***
Latvia	502.47	16.06***	0.02	494.43	25.21***	0.07***
Macedonia	512.02	1.97	0	520.03	12.41***	0.02***
Mexico	446.19	23.8***	0.11***	437.9	24.16***	0.13***
Montenegro	411.3	-1.21***	0	415.77	13.1***	0.03***
Netherlands	514.45	16.15***	0.02	516.63	36.15***	0.11***
Norway	490.84	-2.7***	0	479.49	17.98***	0.03***
New Zealand	522.67	27.7***	0.04***	527.03	37.28***	0.10***
Poland	512.9	18.44***	0.03***	503.57	25.12***	0.08***
Portugal	479.07	28.44***	0.08***	472.84	30.74***	0.14***
Qatar	351.71	-6.93***	0.01***	352.16	3.37***	0.00
Romania	441.19	20.07***	0.05***	434.61	24.23***	0.12***
Russian Federation	494.61	12.53***	0.01***	489.39	20.93***	0.05***
Serbia	446.65	16.02***	0.02	445.03	25.73***	0.08***
Slovak Republic	506.07	21.23***	0.03***	499.82	33.15***	0.11***
Slovenia	517.87	7.04***	0	508.33	29.72***	0.07***
Sweden	501.43	4.45**	0	499.93	21.9***	0.04***
Chinese Taipei	533.51	3.81***	0	544.21	29***	0.06***
Thailand	456.84	22.6***	0.09***	461.28	27.55***	0.13***
Tunisia	414.52	15.52***	0.05***	416.98	18.73***	0.09***
Turkey	457.71	22.13***	0.07***	452.02	25.24***	0.13***
Uruguay	462.11	28.8***	0.08***	453.96	32.76***	0.14***
United States	484.52	31.91***	0.06***	493.65	37.55***	0.12***

*p < .05. **p < .01. ***p < .001.

Table 17 shows the results for the series of multiple regression equations rerun for the two variables associated with economic capital (i.e., Wealth and Home Possessions) and scientific literacy from PISA 2006. The results in Table 17 demonstrate a range across countries of the extent to which the variance in scientific literacy is explained by the variables which comprise social capital. For Wealth, the R^2 values ranges from a low of 0.00 across a number of counties to a high of 0.16 in Mexico (indicating that these variables account for 0% and 16% of the variance in science literacy in these countries respectively). However, these R^2 values were positively skewed and overall the R^2 value was 0.034 for all nations indicating that 3% of scientific literacy was explained by wealth. Additionally, 15 of the 57 counties examined did not have R^2 values that were significantly different from zero at $p<.05$.

For Home Possession, the R^2 values ranges from a low of 0.00 in Qatar to a high of 0.18

in Bulgaria (indicating that these variables account for 0% and 18% of the variance in science literacy in these countries respectively). These R^2 values are normally distributed and overall the value was 0.085 for all nations indicating that 9% of scientific literacy was explained by Home Possessions. Additionally, all of the counties (except Qatar) examined had R^2 values that were significantly different from zero at $p<.05$. This extended analysis would indicate that Home Possession is the stronger and more consistent predictor of economic capital when regressed on scientific literacy for PISA 2006.

Table 18

Results of Regression Analysis by Country for ESCS

$$Science = B_0 + B_1(ESCS) + r$$

Country	Intercept	Index of economic, social and cultural status	R^2
Argentina	416.46	38.29***	0.20***
Australia	519.09	43.01***	0.11***
Austria	502.11	46.04***	0.15***
Azerbaijan	387.6	11.44***	0.05***
Belgium	503.38	47.71***	0.19***
Bulgaria	446.13	51.57***	0.24***
Brazil	423.73	29.5***	0.17***
Canada	524.15	33.13***	0.08***
Switzerland	508.08	44.23***	0.16***
Chile	464.51	37.64***	0.23***
Columbia	411.44	23.23***	0.11***
Czech Republic	511.82	50.82***	0.16***
Germany	504.71	46.45***	0.19***
Denmark	484.7	38.97***	0.14***
Spain	498.72	31.49***	0.14***
Estonia	527.18	31.37***	0.09***
Finland	555.70	31.14***	0.08***
France	502.15	53.7***	0.21***
United Kingdom	508.3	48.44***	0.14***

Greece	479.26	36.51***	0.15***
Hong Kong - China	559.8	25.86***	0.07***
Croatia	497.03	34.45***	0.12***
Hungary	508.15	44.03***	0.21***
Indonesia	425.12	20.81***	0.10***
Ireland	510.09	39.15***	0.13***
Iceland	470.09	28.5***	0.07***
Israel	447.64	42.69***	0.11***
Italy	477.99	30.79***	0.10***
Jordan	438.01	27.09***	0.11***
Japan	533.32	38.79***	0.07***
Kyrgyzstan	340.3	27.1***	0.08***
Korea	522.48	31.56***	0.08***
Liechtenstein	513.38	48.9***	0.20***
Lithuania	486.87	38.16***	0.15***
Luxembourg	483.26	40.98***	0.22***
Latvia	490.78	29.04***	0.10***
Macedonia	523.14	13.33***	0.02***
Mexico	434.76	25.14***	0.17***
Montenegro	412.49	24.47***	0.08***
Netherlands	514.63	43.66***	0.17***
Norway	474.01	35.79***	0.08***
New Zealand	527.67	52.05***	0.16***
Poland	509.97	39.44***	0.14***
Portugal	491.99	28.26***	0.17***
Qatar	348.08	13.52***	0.02***
Romania	431.32	34.66***	0.17***
Russian Federation	482.77	32.24***	0.08***
Serbia	440.39	32.78***	0.13***
Slovak Republic	495.31	44.86***	0.19***
Slovenia	513.33	45.87***	0.17***
Sweden	495.99	38.22***	0.11***
Chinese Taipei	545.9	41.76***	0.13***
Thailand	461.01	27.87***	0.16***
Tunisia	408.27	18.71***	0.10***
Turkey	463.36	30.89***	0.17***
Uruguay	446.02	33.95***	0.18***
United States	482.92	49.19***	0.18***

*p < .05. **p < .01. ***p < .001.

Table 18 shows the results for the series of multiple regression equations run for the variable associated with economic, cultural and social capital and scientific literacy from PISA 2006. This model consists of the PISA index of economic, cultural and social capital (ESCS). The results in Table 18 demonstrate a range across countries of the extent to which the variance in scientific literacy is explained by ESCS. The R^2 values represent a sizable range from a low of

0.02 in Qatar, Macedonia and Lichtenstein to a high of 0.24 in Bulgaria (indicating that these variables account for 2% and 24% of the variance in science literacy in these countries respectively). Overall the R^2 value was 0.13 for all nations indicating that 13% of scientific literacy was explained by the index of economic, social and cultural capital. Again all countries had R^2 values that were significantly different from zero at $p<.05$.

Overview of the Multiple Regression Models for ESCS

Overall, these series of regression equations demonstrated that for all the nations which participated in PISA 2006, of those variable analyzed, cultural capital was the most important explanatory construct for scientific literacy. It accounted for 16% of the variance in scientific literacy scores compared to 14% for social capital, 13% for the composite ESCS and 12% for economic capital. This relatively small value for economic capital would have been further reduced with the removal of one of the independent variables to account for the co-linearity problem. When this was done, 3% of the variance for scientific literacy was accounted for by Wealth and 9% for Home Possessions when they were regressed independently.

Hierarchical Linear Models

Correlations

The correlations between variables at both the student level and the school level were calculated using SYSTAT 11 (Systat Software Inc., Chicago: IL). The correlations at the student level are presented in Tables 18 to 23. At the student level, significant correlations were indicated at a $p< .05$ for all countries after a Bonferroni correction was used in calculating significance. Results for the correlations are presented by country at the student level first, followed by results for each country at the school level.

Student-level correlations. The results for Australia are shown in Table 19. At the student

level, achievement scores in all literacy domains were highly positively correlated (r = 0.79 to 0.89). Looking at the relationships between the student level variables and achievement, positive and moderate correlations were observed between science self- efficacy, science self-concept and ESCS and the achievement domains of mathematics (r = 0.43, 0.41, 0.36)., reading (r = 0.44, 0.35, 0.36) and science (r = 0.50, 0.44, 0.36). Significant correlations between immigrant status and mathematics (r = 0.063) and reading (r = 0.036) achievement that were much lower than these observed n the other student level variables. Immigrant status was found to be non-significantly correlated with science achievement at p<.05(r = 0.009).

Correlations amongst the student level variables followed similar patterns. Science self-efficacy was moderately correlated with science self-concept (r = 0.57), and slightly with ESCS (r = 0.27). Science self-concept was slightly correlated with ESCS (r = 0.20). Immigrant status was correlated with self-efficacy (r = 0.046) and self-concept (r = 0.067) but not significantly correlated with ESCS (r = 0.004).

Table 19

Correlations Between Student-Level Variables and Achievement Scores in All Literacy Domains for Australia*

	1	2	3	4	5	6
1. Immigrant status	1.000*					
2. Science self-efficacy	0.046*	1.000*				
3. Science self-concept	0.067*	0.565*	1.000*			
4. ESCS	0.004	0.274*	0.199*	1.000*		
5. Mathematics	0.063*	0.430*	0.405*	0.357*	1.000*	
6. Reading	0.036*	0.438*	0.346*	0.362*	0.790*	1.000*
7. Science	0.009	0.495*	0.424*	0.357*	0.891*	0.839*

*Correlations are significant at the .05 level.

The results for Canada are shown in Table 20. At the student level, achievement scores in

all literacy domains were high and positively correlated (r = 0.74 to 0.86). Looking at the relationships between the student level variables and achievement, positive and moderate correlations were observed between science self- efficacy, science self-concept and ESCS and the achievement domains of mathematics (r = 0.37, 0.40, 0.32)., reading (r = 0.37, 0.31, 0.32) and science (r = 0.46, 0.42, 0.31). Correlations between immigrant status and mathematics (r = 0.004) and reading (r = 0.003) achievement were much lower than these observed in the other student level variables; however, unlike Australia, these were non-significant. Immigrant status was found to be significantly and negatively correlated with science achievement at p<.05(r = -0.026).

Correlations amongst the student level variables follow: with science self-efficacy moderately correlated with science self-concept (r = 0.50), and slightly with ESCS (r = 0.24); science self-concept was slightly correlated with ESCS (r = 0.20). Immigrant status was correlated with self-efficacy (r = 0.031) and ESCS (r = 0.034) but not significantly correlated with self-concept (r = 0.014).

Table 20

Correlations Between Student-Level Variables and Achievement in All Literacy Domains for Canada*

	1	2	3	4	5	6
1. Immigrant status	1.000*					
2. Science self-efficacy	0.031*	1.000*				
3. Science self-concept	0.014	0.497*	1.000*			
4. ESCS	0.034*	0.237*	0.205*	1.000*		
5. Mathematics	0.004	0.371*	0.399*	0.322*	1.000*	
6. Reading	0.003	0.365*	0.313*	0.316*	0.735*	1.000*
7. Science	-0.026*	0.456*	0.417*	0.306*	0.862*	0.801*

*Correlations are significant at the .05 level.

The results for the Germany are shown in Table 21. At the student level, achievement scores in all literacy domains were highly positively correlated (r = 0.76 to 0.89). Looking at the relationships between the student level variables and achievement, low to moderate correlations were observed between immigrant status, science self- efficacy, science self-concept and ESCS and the achievement domains of mathematics (r = -0.24, 0.39, 0.24, 0.42)., reading (r = -0.23, 0.36, 0.12, 0.38) and science (r = -0.29, 0.44, 0.26, 0.41). Compared to the other countries in this grouping, the negative, significant and 'relatively' higher correlation for immigrant status at the student level are noteworthy.

Immigrant status was also negatively and significantly correlated with science self-efficacy (r = -0.1), science self-concept (r = -0.05) and with ESCS (r = -0.266). Science self-efficacy was moderately correlated with science self-concept (r = 0.49), and slightly with ESCS (r = 0.28). Science self-concept was slightly correlated with ESCS (r = 0.13).

Table 21

Correlations Between Student-Level Variables and Achievement in All Literacy Domains for Germany*

	1	2	3	4	5	6
1. Immigrant status	1.000*					
2. Science self-efficacy	-0.098*	1.000*				
3. Science self-concept	-0.048*	0.489*	1.000*			
4. ESCS	-0.266*	0.280*	0.134*	1.000*		
5. Mathematics	-0.241*	0.385*	0.241*	0.416*	1.000*	
6. Reading	-0.227*	0.359*	0.123*	0.376*	0.763*	1.000*
7. Science	-0.292*	0.438*	0.257*	0.414*	0.891*	0.802*

*Correlations are significant at the .05 level.

The results for New Zealand are shown in Table 22. At the student level, achievement scores in all literacy domains were highly positively correlated and maintained the range seem in

previous countries (r = 0.75 to 0.89). Looking at the relationships between the student level variables and achievement, positive and moderate correlations were observed between science self- efficacy, science self-concept and ESCS and the achievement domains of mathematics (r = 0.44, 0.35, 0.39)., reading (r = 0.44, 0.29, 0.39) and science (r = 0.53, 0.49, 0.41). Significant and negative correlations between immigrant status and reading achievement (r = -0.057) and science (r = -0.056) achievement. Immigrant status was found to be non-significantly correlated with mathematics achievement at p<.05(r = -0.002).

Correlations amongst the student level variables are reported for: science self-efficacy - moderately correlated with science self-concept (r = 0.56), and slightly with ESCS (r = 0.28); science self-concept - slightly correlated with ESCS (r = 0.19). Immigrant status was significantly correlated with self-concept (r = 0.0116) but not significantly correlated with self-efficacy (r = 0.040) and ESCS (r = -0.004).

Table 22

Correlations Between Student-Level Variables and Achievement in All Literacy Domains for New Zealand*

	1	2	3	4	5	6
1. Immigrant status	1.000*					
2. Science self-efficacy	0.040	1.000*				
3. Science self-concept	0.116*	0.558*	1.000*			
4. ESCS	-0.004	0.284*	0.187*	1.000*		
5. Mathematics	-0.002	0.444*	0.349*	0.387*	1.000*	
6. Reading	-0.057*	0.438*	0.292*	0.393*	0.751*	1.000*
7. Science	-0.056*	0.531*	0.382*	0.411*	0.887*	0.830*

*Correlations are significant at the .05 level.

The results for Spain are shown in Table 23. At the student level, achievement scores in all literacy domains were positively correlated (r = 0.69 to 0.85). Looking at the relationships

between the student level variables and achievement, positive and moderate correlations were observed between science self- efficacy, science self-concept and ESCS and the achievement domains of mathematics (r = 0.32, 0.31, 0.34)., reading (r = 0.29, 0.20, 0.29) and science (r = 0.40, 0.34, 0.34). Significant correlations between immigrant status and the achievement domains of mathematics, reading and science were all significantly correlated – but this time negatively (r = -0.150, -0.124, -0.138). Spain demonstrates similar patterns across student level variables and achievement domains; however, the correlation coefficients are noticeable lower for the variables of self-efficacy, self-concept and ESCS yet higher for immigrant status

Among the student level measures, science self-efficacy was moderately correlated with science self-concept (r = 0.42), and slightly with ESCS (r = 0.22). Science self-concept was slightly correlated with ESCS (r = 0.19) and with immigrant status (r = -0.090). Immigrant status was not significantly correlated with self-efficacy and self-concept.

Table 23

Correlations Between Student-Level Variables and Achievement in All Literacy Domains for Spain*

	1	2	3	4	5	6
1. Immigrant status	1.000*					
2. Science self-efficacy	-0.011	1.000*				
3. Science self-concept	0.006	0.421*	1.000*			
4. ESCS	-0.090*	0.217*	0.194*	1.000*		
5. Mathematics	-0.150*	0.318*	0.308*	0.335*	1.000*	
6. Reading	-0.124*	0.292*	0.201*	0.294*	0.683*	1.000*
7. Science	-0.138*	0.397*	0.340*	0.338*	0.849*	0.722*

*Correlations are significant at the .05 level.

Finally, at the student level, the results for the United States are shown in Table 24. Achievement scores in only two literacy domains (mathematics and science) are reported here as

highly positively correlated (r = 0.89). Looking at the relationships between the student level variables and achievement, positive and moderate correlations were observed between science self- efficacy, science self-concept and ESCS and the achievement domains of mathematics (r = 0.33, 0.24, 0.42) and science (r = 0.39, 0.29, 0.41). Additionally, significant correlations between immigrant status and both mathematics (r = -0.115) and science (r = -0.162) achievement. Patterns of correlations between the achievement domains and the student level variables appear to be more similar to these findings with Spain that the other nations in this group.

Science self-efficacy was moderately correlated with science self-concept (r = 0.56), and slightly with ESCS (r = 0.26). Science self-concept was slightly correlated with ESCS (r = 0.217). This time, immigrant status was significantly, negatively and slightly correlated with self-efficacy (r = -0.091), self-concept (r = -0.115) and ESCS (r = -0.254).

Table 24

Correlations Between Student -Level Variables and Achievement in All Literacy Domains for the United States*

	1	2	3	4	5	6
1. Immigrant status	1.000*					
2. Science self-efficacy	-0.091*	1.000*				
3. Science self-concept	-0.050*	0.516*	1.000*			
4. ESCS	-0.254*	0.263*	0.174*	1.000*		
5. Mathematics	-0.115*	0.329*	0.243*	0.421*	1.000*	
6. Reading	na	na	na	na	na	
7. Science	-0.162*	0.391*	0.285*	0.413*	0.892*	na

*Correlations are significant at the .05 level.

School-level correlations. Correlations at the school level are presented in Tables 24 to 29. All school level correlations are school means for each variable; a Bonferroni correction was used in calculating significance.

The results for Australia are shown in Table 25. At the school level, for Australia, all of the relationships between variables are positive and significant. As at the student level, the strongest correlations were among the scores on the academic domains; these correlations ranged from $r = 0.87$ to $r = 0.93$. School ESCS was significantly correlated with the achievement domains of mathematics ($r = 0.721$), reading ($r = 0.692$) and science ($r = 0.747$). School ESCS was also positively correlated with proportion of immigrants in a school ($r = 0.209$) but only slightly. Proportion of immigrants was also correlated with the achievement domains of math, reading and science ($r = 0.247$, 0.200 and 0.151) but again only slightly.

Table 25

Correlations Between School-Level Variables and All Academic Achievement Domains for Australia*

	1.	2.	3.	4.	5.
1. School ESCS	1.000*				
2. Proportion immigrants	0.209*	1.000*			
3. Mathematics	0.721*	0.247*	1.000*		
4. Reading	0.692*	0.200*	0.872*	1.000*	
5. Science	0.747*	0.151*	0.930*	0.894*	1.000*

*Correlations are significant at the .05 level.

The results for Canada are shown in Table 26 and a similar pattern are evident from that observed n Australia. Almost of the relationships between variables are positive and significant. The strongest correlations were among the scores on the academic domains: mathematics and reading ($r = 0.810$); mathematics and science ($r = 0.876$) and reading and science ($r = 0.872$). School ESCS was significantly correlated with the achievement domains of mathematics ($r = 0.564$), reading ($r = 0.568$) and science ($r = 0.568$). School ESCS was also positively correlated with proportion of immigrants in a school ($r = 0.244$). Proportion of immigrants was slightly correlated with the achievement domains of reading and science ($r = 0.115$ and 0.058) but not

with mathematics.

Table 26

Correlations Between School-Level Variables in All Literacy Domains for Canada*

	1.	2.	3.	4.	5.
1. School ESCS	1.000*				
2. Proportion immigrants	0.244*	1.000*			
3. Mathematics	0.564*	0.090	1.000*		
4. Reading	0.568*	0.115*	0.810*	1.000*	
5. Science	0.568*	0.058	0.876*	0.872*	1.000*

*Correlations are significant at the .05 level.

The results for Germany – as has been noted previously – are different from what has been seen so far (Table 27). Although all of the relationships between variables are significant, negative relationships with proportion of immigrants are observed. Correlations on the academic domains were high and ranged from $r = 0.90$ to $r = 0.96$. School ESCS was significantly correlated with the achievement domains of mathematics ($r = 0.835$), reading ($r = 0.773$) and science ($r = 0.840$). School ESCS was negatively correlated with proportion of immigrants in a school ($r = -0.477$). Proportion of immigrants was also negatively and moderately correlated with the achievement domains of math, reading and science ($r = -0.496$, -0.452 and -0.526).

Table 27

Correlations Between School-Level Variables in All Literacy Domains for Germany*

	1.	2.	3.	4.	5.
1. School ESCS	1.000*				
2. Proportion immigrants	-0.477*	1.000*			
3. Mathematics	0.835*	-0.496*	1.000*		
4. Reading	0.773*	-0.452*	0.900*	1.000*	
5. Science	0.840*	-0.526*	0.956*	0.960*	1.000*

*Correlations are significant at the .05 level.

The results for New Zealand are shown in Table 28. Strong correlations exist among the scores on the academic domains and ranged from $r = 0.75$ to $r = 0.87$. Similar – if not quite as strong - correlations for school ESCS with the achievement domains of mathematics ($r = 0.733$), reading ($r = 0.685$) and science ($r = 0.794$) are also observed. School ESCS was also positively correlated with proportion of immigrants in a school ($r = 0.146$). Proportion of immigrants was also slightly correlated with the achievement domains of math, and reading ($r = 0.070$ and 0.044) and negatively with science ($r = -0.019$).

Table 28

Correlations Between School-Level Variables in All Literacy Domains for New Zealand*

	1.	2.	3.	4.	5.
1. School ESCS	1.000*				
2. Proportion immigrants	0.146	1.000*			
3. Mathematics	0.733*	0.070	1.000*		
4. Reading	0.685*	0.044	0.754*	1.000*	
5. Science	0.794*	-0.019	0.869*	0.866*	1.000*

*Correlations are significant at the .05 level.

The results for Spain are shown in Table 29. The pattern appears to mirror those uncovered for Germany. At the student level, the strongest correlations were among the scores on the academic domains; these correlations ranged from $r = 0.73$ to $r = 0.85$. School ESCS was significantly correlated with the achievement domains of mathematics ($r = 0.611$), reading ($r = 0.523$) and science ($r = 0.607$). School ESCS was negatively correlated with proportion of

immigrants in a school (r = -0.210) as well as the academic domains of math (r = -0.372), reading (r = -0.239) and science (r = -0.337).

Table 29

Correlations Between School-Level Variables in All Literacy Domains for Spain*

	1.	2.	3.	4.	5.
1. School ESCS	1.000*				
2. Proportion immigrants	-0.210*	1.000*			
3. Mathematics	0.611*	-0.372*	1.000*		
4. Reading	0.523*	-0.239*	0.733*	1.000*	
5. Science	0.607*	-0.337*	0.849*	0.734*	1.000*

*Correlations are significant at the .05 level .

Lastly, the results for the United States are shown in Table 30. Because reading achievement was not documents for this country, the correlation between mathematics and science achievement was high at r = 0.935. School ESCS was also significantly correlated with the achievement domains of mathematics (r = 0.762), and science (r = 0.765). School ESCS was negatively correlated with proportion of immigrants in a school (r = -0.400). Proportion of immigrants was also negatively correlated with the achievement domains of math, and science (r = 0.281, and 0.295) but only slightly.

Table 30

Correlations Between School-Level Variables in All Literacy Domains for the United States*

	1.	2.	3.	4.	5.
1. School ESCS	1.000*				
2. Proportion immigrants	-0.400*	1.000*			
3. Mathematics	0.762*	-0.281*	1.000*		
4. Reading	na	na	na	na	
5. Science	0.765*	-0.295*	0.935*	na	1.000*

*Correlations are significant at the .05 level.

Summary of correlation analysis. At the student level, the correlations between science, mathematics and reading literacy were consistently high and significant; in the range of 0.8 with science and mathematics literacy consistently being the largest. Moderate and significant correlations were reported here between the student level variables (science self-concept, science self-efficacy and ESCS) and the three literacy measures as well as among themselves (in the range of 0.3 to 0.4). Science self-concept and science self-efficacy significantly correlated in the 0.5 range. Immigrant status was noticeable lower, being often correlated with these other student level variables at < 0.1, negative and non-significant. At the school level, mathematics, reading and science literacy were all positively, strongly and significantly correlated with each other (close to $r = 0.8$). School ESCS also strongly, significantly and positively correlated with these literacy measures and significantly but only slightly with proportion of immigrants. However, proportion of immigrants at the school level tended to be only slightly correlated with the other measures and often either negative or non-significantly different from zero. Germany was the exception where proportion of immigrants was negatively, moderately and significantly correlated with the other variables.

Multilevel Models

Analysis in this section was expanded to include multilevel analysis on outcome measures with science self-efficacy, science self-concept, socioeconomic status and immigrant status as predictors at the student level and school ESCS and school proportion of immigrants at

the school level. As stated previously, this type of regression analysis allows for the partitioning of variance between the levels of the model (i.e., student and school). I used a two-level (schools in countries) hierarchical linear model (HLM; Byrk & Raudenbush, 2002) to investigate further the relationship between mathematics, reading and literacy achievement for Australian, Canadian, German, New Zealand, Spanish and American students on PISA 2006. In the situation with the PISA data, HLM uses level-1 student and level-2 school variables to help explain variation in achievement scores while accounting for the variance at each level. HLM allows for estimating both the effects of group-level variables on school mean score and on the slopes of the individual characteristics to predict outcome variables (Willms & Smith, 2005). HLM is also useful here for its ability to analyze both sample weights and plausible values, both of which are employed in all PISA analysis. Sample weights are used to account for the stratified sample design in PISA and also to ensure that population parameter estimates are unbiased (OECD, 2006).

The results of the HLM models for the countries selected are presented in Tables 30 to 48 and in Appendix H. As commented previously, final estimates in each HLM are the average results from analysis of the five plausible values with final student weights taken into account (Mislevy, Johnson, & Muraki, 1992). The final model is derived by removing the school-level variables and error terms with non-significant coefficients and the student-level variables with non-significant intercepts and negligible error variances and then rerunning HLM. Only the values of the significant fixed effects and random effects are presented in the final tables.

Building and estimating. The first analysis was to estimate the unconditional model with no Level 1 predictors to determine the total amount or variability on the three achievement measures within and between schools. The calculation of this piece of empirical evidence is

provided for by the intraclass correlation coefficient (ICC), a measure of the proportion of variance in the dependent variable accounted for by the level-2 predictors. The intraclass correlation coefficient is detailed as,

$$\rho = \tau_{00} \Big/ \tau_{00} + \sigma^2$$

Where τ_{00} and σ^2 are estimates of the level-1 and level-2 error variance and can be obtained by fitting a null model using HLM software. Snijders and Bosker (1999) refer to the ICC as the degree of resemblance between micro-units belonging to the same macros unit, students in schools, and in the case of the model provided would indicate the amount of variance in the model attributable to school level difference. The outputs for the null models also demonstrate whether the schools mean math scores (β_{0j}) vary across schools and provides estimates of the grand means of the mathematics, reading and science literacy scores (γ_{00}). The null model is unconditioned in that no student or school level variables are entered in the model. However, schools are modeled to vary in terms of average performance.

The equations of the Null Models are,

Student level (Level 1): $Y_{ij} = \beta_{0j} + r_{ij}$

School level (Level 2): $\beta_{0j} = \gamma_{00} + u_{0j}$

where Y_{ij}, is the achievement score for student *i* and school *j*;

β_{0j} is the achievement score intercept, and it is calculated for each of *j* schools in the dataset;

r_{ij} is unique error associated with the student *i* and school *j*;

γ_{00} is mean achievement for all the students in the sample; and

u_{0j} is the unique error to the intercept associated with school *j*.

The outputs of the Null models are given in Appendix H. These tables are organized by domain,

with each country's null model provided. A summary of the intraclass correlations (the proportion of variance in scores accounted for by schools) is provided in Table 31.

Table 31

Intraclass Correlations (ICC) Derived from the Null Models for All Countries and All Domains

Country	ICC for science literacy	ICC for mathematics literacy	ICC for reading literacy
Australia	.19	.23	.23
Canada	.20	.22	.25
Germany	.57	.61	.68
New Zealand	.17	.16	.20
Spain	.18	.19	.21
The United States	.23	.29	na

The null models – as summarized in both Table 31 and detailed in Appendix H – produce useful preliminary information. First, they provide an estimation of the grand mean for each country and each domain (e.g., 524.63 for science literacy for Australia). At the student level, Byrk and Raudenbush (2002) suggest that to gauge the variation among schools a plausible value range can be calculated for each country level grand mean based upon a 95% confidence interval using the equation $\gamma 00 \pm 1.96\sqrt{\tau 00}$. For Australia and the domain of science literacy this would yield a range of 511.7 to 537.56 average achievement levels among schools. Second, these null models offer a way to partition the total variation in achievement across the domain of interest into variation between and within schools. In Table 31 (above) we can see that the amount of variance that can be modeled at the school level across all domains and all countries is in the 20% range (except for Germany which falls closer to 60%). This means that in Germany, approximately 60% of a student's expected general ability score for all domains will be strongly influenced by the school that student attends (leaving 40% of the variability accounted for by

other factors, such as student attitudes and beliefs), while in Canada, just over 20% of a student's expected general ability score will be influenced by the school that student attends, with the remaining variability at the student level. This partitioning of variance will provide a useful reference as variables are entered into each level of the model.

Random Coefficient Model

Although there is no 'correct' way to build a multilevel model, a typical approach is to build from the bottom up (Byrk & Raudenbush, 2002). In the next series of HLM models – really an intermediary step to the final model - student-level variables were added to examine the estimated within-school variance, which is the proportion of the variance in achievement scores that can be accounted for by the student-level variables (i.e., science self-efficacy, science self-concept, ESCS and immigrant status). All student-level variables were entered into the equations uncentered, and the estimated coefficients showed the within-school achievement score difference, controlling for other student-level variables. These models were then compared to the null model by examining the proportion of unexplained within-school variance that was accounted for after all the student-level predictors were included in the model (see Table 32).

The following is an example of this random coefficient model for general science achievement for Australia. It includes all of the student level variables being examined in this section of the study.

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{IMMGRANT}) + \beta_{2j}(\text{EFFICACY}) + \beta_{3j}(\text{CONCEPT}) + \beta_{4j}(\text{ESCS}) + r_{ij}$$

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + u_{1j}$$

$$\beta_{2j} = \gamma_{20} + u_{2j}$$

$$\beta_{3j} = \gamma_{30} + u_{3j}$$

$\beta_{4j} = \gamma_{40} + u_{4j}$

where β_{1j} to β_{4j} are the parameters of the student-level variables of interest; and

γ_{00} to γ_{40} are the average regression slopes across students.

u_{0j} to u_{4j} is the error term unique to school $_j$

Any non-significant student level predictors as well as non significant intercept or slope variance terms were also removed from the model at this stage. Although these *Random Coefficient Models* will not be depicted here in any detail, the estimated within-school variance reduction (p) has been provided in Table 32 for reference. What this amounts to is an index of the proportion of the variance in achievement scores that can be accounted for by the student-level variables (i.e., science self-efficacy, science self-concept, ESCS and immigrant status) at Level 1 by comparing the σ^2 estimates from the null and random coefficients model (Byrk & Raudenbush, 2002). The equation is,

$$p = \sigma^2_{null} - \sigma^2_{random coefficients} \Big/ \sigma^2_{null}$$

Table 32

Estimated Variance Reduction Within-School Variance From the Random Coefficient Models for All Countries Across All Domains

Country	Within-school variance for science literacy	Within-school variance for mathematics literacy	Within-school variance for reading literacy
Australia	.31	.24	.25
Canada	.30	.26	.22
Germany	.22	.17	.08
New Zealand	.37	.28	.29
Spain	.27	.23	.20
The United States	.25	.20	na

We can see in Table 32 that adding the student-level variables of science self-efficacy, science self-concept, ESCS and immigrant status as predictors of science, mathematics or reading literacy reduced the within-school variance by approximately 20 to 30% (with the obvious exception of Germany that was lower than the other nations potentially because they had a much smaller proportion of variance to model at the student level). We can conclude that the combination of the student-level variables of science self-efficacy, science self-concept, ESCS and immigrant status account for about 25% of the student-level variance in the outcome.

Random Intercept and School Slope Models

The last stage of this HLM analyses produces final models by adding school-level variables (school mean ESCS and proportion of immigrants in the school) which examines if student achievement varied due to both the Level 1 and Level 2 variables. Initially, the slopes for these variables were allowed to vary in the models. This model was used to answer which variables significantly explain the achievement variance across schools for all nations selected and for all three literacy domains. Below is an example of a preliminary random intercept and school slopes model for science achievement in Australia based upon PISA 2006.

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{IMMGRANT}) + \beta_{2j}(\text{EFFICACY}) + \beta_{3j}(\text{CONCEPT}) + \beta_{4j}(\text{ESCS}) + r_{ij}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + \gamma_{02}(\text{PROIMMIG}) + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}(\text{SCHESCS}) + \gamma_{12}(\text{PROIMMIG}) + u_{1j}$$

$$\beta_{2j} = \gamma_{20} + \gamma_{21}(\text{SCHESCS}) + \gamma_{22}(\text{PROIMMIG}) + u_{2j}$$

$$\beta_{3j} = \gamma_{30} + \gamma_{31}(\text{SCHESCS}) + \gamma_{32}(\text{PROIMMIG}) + u_{3j}$$

$$\beta_{4j} = \gamma_{40} + \gamma_{41}(\text{SCHESCS}) + \gamma_{42}(\text{PROIMMIG}) + u_{4j}$$

After non-significant variables were removed, the final model was:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{IMMGRANT}) + \beta_{2j}(\text{EFFICACY}) + \beta_{3j}(\text{CONCEPT}) + \beta_{4j}(\text{ESCS}) + r_{ij}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01}\,(\text{SCHESCS}) + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}\,(\text{PROIMMIG}) + u_{1j}$$

$$\beta_{2j} = \gamma_{20} + u_{2j}$$

$$\beta_{3j} = \gamma_{30} + \gamma_{31}\,(\text{SCHESCS}) + u_{3j}$$

$$\beta_{4j} = \gamma_{40} + u_{4j}$$

Scientific literacy. This final model for science literacy in Australia (above) indicates that for the intercept (β_{0j}: school average science achievement), school level ESCS (SCHESCS) was significant at Level 2, and that there was significant variability across schools (because the error term (u_{0j}) is still in the model for the intercept). There was also significant variability across schools for the immigrant, self-efficacy, self-concept and socio-economic slopes. This final model for Australia is numerically depicted in Table 33. From this table, students who are native to Australia, have higher reported scores for self-efficacy and self-concept and who come from homes with higher socioeconomic status will attain higher science literacy scores on PISA. Keeping in mind that coefficients are conditioned by the model and any increase assumes the other variables remain constant. Specifically, as the value of immigrant status increases by one unit, science achievement score is predicted to decrease by 23 points with all other variables held constant, and for self-efficacy and self-concept, a one unit increase predicts a 26.42 and 21.34 point increase respectively. A one unit increase in ESCS translates to a predicted increase of 14.99 units in science literacy. These results are interpreted with all other variables held constant.

Additionally, at the school level, attending a school with a one unit greater mean ESCS will increase the intercept value predicted school mean score (originally 519.99) by almost 49 units (half a standard deviation). The student immigrant slope is also made steeper by attending a school with a larger portion of immigrant by 25.67 units if you move from a school with no

immigrants to all immigrants. The change would be 2.57 units for a proportional increase of 10%. Finally, the self-concept slope in increased by 5.92 units as the school mean ESCS increases by one unit. Again, these results are interpreted individually with all other variables held constant. There was significant school variation in average school scores after controlling for school ESCS. The immigrant slope, science self-efficacy slope and the ESCS slope all varied significantly across schools.

Table 33

Final Model for Scientific Literacy for Australia

Variables	Parameters estimate				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed effects					
Science intercept (γ_{00})	519.99	1.83	284.65	313	.000
School ESCS (γ_{01})	48.97	4.30	11.39	353	.000
Immigrant Slope					
Intercept (γ_{10})	-22.76	4.65	-4.89	353	.000
Proportion immigrants (γ_{11})	25.67	11.52	2.23	353	.000
Self-efficacy slope					
Intercept (γ_{20})	26.42	1.04	25.46	354	.000
Self-concept slope					
Intercept (γ_{30})	21.34	1.33	16.09	353	.000
School ESCS (γ_{31})	5.92	2.51	2.36	47	.000
ESCS slope					
Intercept (γ_{40})	14.99	1.44	10.41	289	.000
	Variance				
Random effects	component	*SD*	χ^2	*df*	*p*
Intercept (u_0j)	370.37	19.24	650.23	305	.000
Immigration slope (u_1j)	305.64	17.48	389.92	305	.001
Science self-efficacy slope (u_2j)	55.43	7.45	372.87	306	.005

Science self-concept slope (u_3j)	48.15	6.94	371.80	305	.005
ESCS slope (u_4j)	66.65	8.16	369.21	305	.008
Student-level effect (r)	5,708.69	75.56			

Note. Proportion of variance explained in intercept (β_0) = 0.45; immigrant slope (β_1) = 0.09; self-concept slope (β_3) = 0.18.

Similar to the index of the proportion of the variance in achievement scores accounted for by the student-level variables that was documented in Table 33 we can develop a proportional reduction in variance for random coefficients (intercepts and slopes) from the Level-1 model (Byrk & Raudenbush, 2002). The equation for this statistic is,

$$p = \tau_{00}(randomANOVA) - \tau_{00}(Level2model) \Big/ \tau_{00}(randomANOVA)$$

The values for Australia and science literacy indicate that there is a sizable reduction in variance of the school means once School ESCS is controlled. The unconditional variance of school intercepts (τ_{00}) had been 676.27 and the residual variance is now 370.77. This means that 45% of the variation in mean achievement (conditioned by level 1 and 2 predictors) has been explained by School ESCS [i.e., (676.27-370.77)/676.27 = 0.45]. Additionally, the residual variance of the immigrant slope and the science self-concept slope are reduced by 9% and 18% respectively. Proportional reduction in variance for random coefficients for all nations in this study can be found at the bottom of their respective final model table.

Table 34 shows that for science achievement in Canada, at the student-level model, students who are native, have higher reported scores for self-efficacy and self-concept and who come from homes with higher socioeconomic status will attain greater achievement scores. Specifically, as the value of immigrant status increases by one unit, science achievement score is predicted to decrease by 21.24 points, and for self-efficacy and self-concept, a one unit increase predicts a 22.25 and 19.68 point increase respectively. A one using increase in ESCS translates to

a predicted increase of 12.99 units in science literacy. These results are interpreted singularly with all other variables held constant.

As school mean ESCS increased by one unit, the school average score on science literacy score increased by 42.39 points with other variables held constant. There was also significant school variation in average school scores after controlling for school ESCS. For Canada, 22% of the variation in mean achievement for science has been explained by School ESCS.

Table 34

Final Model for Scientific Literacy for Canada

Variables	Parameters estimate				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed effects					
Science intercept (γ_{00})	513.17	1.42	360.50	894	.000
School ESCS	42.39	5.88	7.20	893	.000
Immigrant slope					
Intercept (γ_{10})	-21.24	3.33	-6.38	278	.000
Self-efficacy slope					
Intercept (γ_{20})	25.25	1.37	18.48	63	.000
Self-concept slope					
Intercept (γ_{30})	19.68	1.22	16.08	168	.000
ESCS slope					
Intercept (γ_{40})	12.99	1.77	7.33	269	.000
Random effects	Variance component	*SD*	χ^2	*df*	*p*
Intercept (u_0j)	1,267.43	35.60	4,631.09	463	.000
Immigration slope (u_1j)	1,091.73	33.04	845.80	464	.000
Science self-efficacy slope (u_2j)	77.62	8.81	853.96	464	.000
Science self-concept slope (u_3j)	107.79	10.38	846.61	464	.000
ESCS slope (u_4j)	48.69	6.97	720.65	463	.000

Student-level effect (*r*)	5,406.42	73.53

Note. Proportion of variance explained in intercept (β_0) = 0.22.

The student-level model for science achievement in Germany (Table 35) - intercept 493.20 - indicates a higher impact for immigrant status (-36.87) but lower impacts of science self-efficacy, science self-concept and ESCS (18.77, 12.08 and 6.61) relative to the other models in this study. These changes are based upon single increases in the student level variables and hold true when all other variables are held constant.

For the school-level model, school ESCS significantly influenced the intercept in the final HLM model. As school mean ESCS increased by one unit, the school average score on science literacy score increased by a sizable 92.94 points with other variables held constant. There was also significant school variation in average school scores after controlling for school ESCS. For Germany, a sizable 64% of the variation in mean achievement for science has been explained by School ESCS.

Table 35

Final Model for Scientific Literacy for Germany

Variables	Parameters estimate				
	Coefficient	*SE*	*t*	*df*	*P*
Fixed effects					
Science intercept (γ_{00})	493.20	3.34	147.79	210	.000
School ESCS (γ_{01})	92.94	6.11	15.21	210	.000
Immigrant slope					
Intercept (γ_{10})	-36.87	3.99	-9.24	128	.000
Self-efficacy slope					
Intercept (γ_{20})	18.77	1.33	14.06	433	.000
Self-concept slope					

Intercept (γ_{30})	12.08	1.29	9.38	215	.000
ESCS slope					
Intercept (γ_{40})	6.61	1.38	4.77	915	.000

Random effects	Variance component	*SD*	χ^2	*df*	*P*
Intercept (u_0j)	1,177.75	34.32	1,558.83	210	.000
Student-level effect (*r*)	3,657.99	60.48			

Note. Proportion of variance explained in intercept (β_0) = 0.64.

The student-level model for science achievement in New Zealand (Table 36) paints a more complex picture than previously uncovered. This final model shows the same pattern of negative impact for a unit increase in immigrant status and positive impact for unit increases in self-efficacy, self-concept and ESCS. Specifically, as the value of immigrant status increases by one unit, the science achievement score is predicted to decrease by almost 23 points. For science self-efficacy and science self-concept, a one unit increase predicts a 37.75 and 13.61 point increase respectively. A one using increase in ESCS translates to a predicted increase of 19.46 units in science literacy. These results are interpreted singularly with all other variables held constant.

At the school-level model, School level ESCS and proportion of immigrants in the school were found to be significant. The estimated science intercept of 535.05 was positively influenced by 54.61 points for school ESCS. That is, as schools mean ESCS score increased by one unit the science achievement score for a student in that school would increase, on average, by 54.61 units. The student science self-concept slope (a positive value of 13.61) was further steepened 14.22 unit by an increase in school mean ESCS. Finally, the ESCS slope in influenced by both school ESCS and proportion immigrants. What these numbers indicate is that the slope of 19.46 for ESCS is decreased (flattened) for schools with higher means ESCS (i.e., the impact is not a

great); however, a 100% increase in the proportion of immigrants in a school would make the ESCS slope even steeper by 26.39 units. There was significant school variation in average school scores after controlling for students' ESCS. Additionally, the science self-efficacy and science self-concept slopes varied between schools in this model. The variation in mean achievement for New Zealand that has been explained by School ESCS is 0.51 or 51%. Additionally, the residual variance on science self-concept slope is reduced by 23% when conditioned for School ESCS.

Table 36

Final Model for Scientific Literacy for New Zealand

Variables	Parameters estimate				
	Coefficient	*SE*	*t*	*df*	*P*
Fixed effects					
Science intercept (γ_{00})	535.05	2.51	213.46	168	.000
School ESCS (γ_{01})	54.61	5.32	10.26	168	.000
Immigrant slope					
Intercept (γ_{10})	-22.61	3.67	-6.17	1,984	.000
Self-efficacy slope					
Intercept (γ_{20})	37.75	1.83	20.57	84	.000
Self-concept slope					
Intercept (γ_{30})	13.61	2.06	6.63	168	.000
School ESCS (γ_{31})	14.22	4.17	3.41	168	.001
ESCS slope					
Intercept (γ_{40})	19.46	2.68	7.26	474	.000
School ESCS (γ_{41})	-11.65	4.16	-2.80	1,908	.006
Proportion immigrant (γ_{42})	26.39	7.97	3.31	473	.001
	Variance				
Random effects	component	*SD*	χ^2	*df*	*P*
Intercept (u_0j)	405.34	20.13	393.18	167	.000

Science self-efficacy slope (u_2j)	54.60	7.39	216.14	168	.007
Science self-concept slope (u_3j)	96.51	9.82	212.72	167	.010
Student-level effect (r)	6,191.57	78.69			

Note. Proportion of variance explained in intercept (β_0) = 0.51; self-concept slope (β_3) = 0.23.

The student-level model for general scientific literacy in Spain (Table 37) continues the same trend for student-level predictors. As student immigrant status increases by unit, the science achievement assessment score is predicted to decrease by 42.63 points. As science self-efficacy, self-concept and ESCS increases by one unit, students are predicted to score 22.63, 15.08 and 14.75 points higher on the science literacy assessment. For all of these results, they hold true when all other variables are held constant.

Table 37

Final Model for Scientific Literacy for Spain

Variables	Parameters estimate				
	Coefficient	*SE*	*t*	*df*	*P*
Fixed effects					
Science intercept (γ_{00})	505.89	1.99	253.37	684	.000
School ESCS (γ_{01})	21.68	2.89	7.94	684	.000
Immigrant slope					
Intercept (γ_{10})	-42.63	5.05	-8.37	590	.000
Self-efficacy slope					
Intercept (γ_{20})	22.63	1.07	21.08	327	.000
Self-concept slope					
Intercept (γ_{30})	15.08	1.15	21.08	327	.000
School ESCS (γ_{31})	3.67	1.85	1.98	193	.048
ESCS slope					
Intercept (γ_{40})	14.75	1.19	12.37	368	.000

Random effects	Variance component	*SD*	χ^2	*df*	*P*
Intercept (u_0j)	506.15	22.49	1,366.87	335	.000
Immigration slope (u_1j)	1,633.39	40.41	588.39	336	.000
Science self-efficacy slope (u_2j)	18.69	4.32	458.52	336	.000
Science self-concept slope (u_3j)	47.18	6.86	526.28	335	.000
ESCS slope (u_4j)	39.22	6.26	482.51	336	.000
Student-level effect (*r*)	4,889.75	69.92			

Note. Proportion of variance explained in intercept (β_0) = 0.22; self-concept slope (β_3) = 0.02.

For the school-level model, the aggregated schools mean ESCS was significant in the final HLM model. One unit increases in schools mean ESCS impacted the original intercept of 505.89 for science literacy positively by 21.68 units. Further, a schools mean ESCS increase of one unit, also positively impacted the science self-concept slope by 3.67 points. There was significant school variation in average school scores after controlling for school ESCS. The science self-efficacy slope and the ESCS slope varied significantly across schools. The variation in mean achievement for Spain that has been explained by the addition of School ESCS is 22% as well as 2% of science self concept.

Table 38

Final Model for Scientific Literacy for the United States

Variables	Parameters estimate				
	Coefficient	*SE*	*t*	*df*	*P*
Fixed effects					
Science intercept (γ_{00})	477.39	4.10	116.36	164	.000
School ESCS (γ_{01})	44.39	8.23	5.39	164	.000

Immigrant slope					
Intercept (γ_{10})	-17.07	4.50	-3.79	164	.000
Self-efficacy slope					
Intercept (γ_{20})	22.92	1.57	14.63	165	.000
Self-concept slope					
Intercept (γ_{30})	11.52	1.51	7.65	96	.000
School ESCS (γ_{31})	13.03	2.61	4.99	46	.000
ESCS slope					
Intercept (γ_{40})	21.59	1.87	11.51	115	.000

Random effects	Variance component	*SD*	χ^2	*df*	*P*
Intercept (u_0j)	1,034.94	32.17	525.83	117	.000
Immigrant slope (u_1j)	327.01	18.08	160.34	118	.006
Science self-efficacy slope (u_2j)	58.15	7.63	185.51	118	.000
Student-level effect (*r)*	6,399.07	79.99			

Note. Proportion of variance explained in intercept (β_0) = 0.37.

The student-level model for science achievement in the United States is presented above in Table 38. This final model shows the same pattern of negative impact for a unit increase in immigrant status and positive impact for unit increases in self-efficacy, self-concept and ESCS. Specifically, as the value of immigrant status increases by one unit, the science achievement score is predicted to decrease by 17.07 points. For science self-efficacy and science self-concept, a one unit increase predicts a 22.92 and 11.52 point increase respectively. A one unit increase in ESCS translates to a predicted increase of 21.59 units in science literacy. These results are interpreted singularly with all other variables held constant.

At the school-level model, school level ESCS was found to significantly influence the prediction of science achievement. The estimated science intercept of 535.05 was positively influenced by 44.39 points for a 1 unit change in school ESCS. The student science self-concept

slope (a positive value of 11.52) increased by 13.03 units for every unit increase in school mean ESCS. There was significant school variation in average school scores after controlling for students' ESCS. Additionally, the immigrant slope and science self-efficacy slope varied between schools in this model. For the United States, 37% of the variation in mean achievement for science has been explained by the addition of School ESCS.

Mathematics literacy. The final model for Australia is detailed in Table 39. From this table, students who are native to Australia, have higher reported scores for self-efficacy and self-concept and who come from homes with higher socioeconomic status will attain higher mathematics literacy scores on PISA. Interestingly, immigrant status does not have a significant impact at the student level. Specifically, a unit increase in self-efficacy and self-concept, a one unit increase predicts a 16.39 and 20.20 point increase respectively. A one using increase in ESCS translates to a predicted increase of 13.79 units in mathematics literacy. These results are interpreted singularly with all other variables held constant.

Additionally, at the school level, attending a school with a one unit greater mean ESCS will increase the intercept value (originally 509.97) by almost 50 units (again, half a standard deviation). A 1-point shift in school level ESCS is a large shift given the SD of the school level ESCS values (e.g., SD=0.41 for Australia). The self-concept slope increases by 6.21 units as the school mean ESCS increases by one unit. Again, these results are interpreted individually with all other variables held constant. There was significant school variation in average school scores after controlling for school ESCS. The science self-efficacy slope and the science self-concept slope all varied significantly across schools. The variation in mean achievement for Australia that has been explained by School ESCS is 39%. Additionally, the residual variance on science self-concept slope is also reduced by 20% when conditioned for School ESCS.

Table 39

Final Model for Mathematics Literacy for Australia

Variables	Parameters estimate				
	Coefficient	*SE*	*t*	*df*	*P*
Fixed effects					
Science intercept (γ_{00})	509.97	1.96	260.49	353	.000
School ESCS (γ_{01})	49.50	4.88	10.15	353	.000
Self-efficacy slope					
Intercept (γ_{20})	16.39	0.97	16.85	230	.000
Self-concept slope					
Intercept (γ_{30})	20.20	1.31	15.46	53	.000
School ESCS (γ_{31})	6.21	2.39	2.60	46	.013
ESCS slope					
Intercept (γ_{40})	13.79	1.25	11.02	202	.000
Random effects	Variance component	*SD*	χ^2	*df*	*p*
Intercept (u_0j)	569.79	23.87	1,500.68	350	.000
Science self-efficacy slope (u_2j)	35.44	5.95	470.74	351	.000
Science self-concept slope (u_3j)	39.59	6.29	446.00	350	.001
Student-level effect (*r*)	4,587.26	67.73			

Note. Proportion of variance explained in intercept (β_0) = 0.39; self-concept slope (β_2) = 0.20.

Table 40 shows that for mathematics achievement in Canada, at the student-level model, students who are native, have higher reported scores for self-efficacy and self-concept and who come from homes with higher socioeconomic status will attain greater achievement scores. Specifically, as the value of immigrant status increases by one unit, mathematics achievement score is predicted to decrease by 9.81 points, and for self-efficacy and self-concept, a one unit increase predicts a 15.20 and 19.69 point increase respectively. A one using increase in ESCS translates to a predicted increase of 12.42 units in mathematics literacy. These results are

interpreted singularly with all other variables held constant.

Table 40

Final Model for Mathematics Literacy for Canada

Variables	Parameters estimate				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed effects					
Science intercept (γ_{00})	508.35	3.06	166.43	832	.000
School ESCS (γ_{01})	29.12	5.98	4.87	624	.000
Immigrant slope					
Intercept (γ_{10})	-9.81	3.20	-3.06	144	.003
Self-efficacy slope					
Intercept (γ_{20})	15.20	1.16	13.10	331	.000
Self-concept slope					
Intercept (γ_{30})	19.69	1.09	18.12	147	.000
ESCS slope					
Intercept (γ_{40})	12.42	1.33	9.32	894	.000
Random effects	Variance component	*SD*	χ^2	*df*	*p*
Intercept (u_0j)	974.07	31.21	1,327.51	463	.000
Immigration slope (u_1j)	1,045.61	32.35	836.55	464	.000
Science self-efficacy slope (u_2j)	63.47	7.96	887.59	464	.000
Science self-concept slope (u_3j)	78.26	8.85	798.86	464	.000
ESCS slope (u_4j)	65.11	8.07	755.06	464	.000
Student-level effect (r)	4,331.81	65.82			

Note. Proportion of variance explained in intercept (β_0) = 0.08.

At the school-level model, school level ESCS was found to significantly influence the prediction of mathematics achievement. The estimated mathematics intercept of 508.35 was positively influenced by 29.12 points for school ESCS. There was significant school variation in

average school scores after controlling for students' ESCS. Additionally, the science self-efficacy slope, science self-concept slope and ESCS slope varied between schools in this model. For Canada, a paltry 8% of the variation in mean school achievement for mathematics has been explained by the addition of School ESCS.

The multilevel model for mathematics achievement in Germany (Table 41) was more similar to the other nations in this domain than previously encountered with science results for Germany. At the student-level, students who are native, have higher reported scores for self-efficacy and self-concept and who come from homes with higher socioeconomic status will attain greater achievement scores. Specifically, as the value of immigrant status increases by one unit, mathematics achievement score is predicted to decrease by a sizable 21.57 points, and for self-efficacy and self-concept, a one unit increase predicts an 11.07 and 12.85 points increase respectively. A one using increase in ESCS translates to a predicted increase of 7.97 units in mathematics literacy. These results are interpreted with all other variables held constant.

For the school-level model, school ESCS significantly influenced the intercept in the final HLM model. As school mean ESCS increased by one unit, the school average score on mathematics literacy score increased by a sizable 100.64 points with other variables held constant. For the Germany, 63% of the variation in mean achievement for mathematics has been explained by the addition of School ESCS.

Table 41

Final Model for Mathematics Literacy for Germany

Variables	Parameters estimate				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed effects					
Science intercept (γ_{00})	476.85	3.51	135.98	210	.000

School ESCS (γ_{01})	100.64	6.29	15.99	210	.000
Immigrant slope					
Intercept (γ_{10})	-21.57	3.38	-6.39	482	.000
Self-efficacy slope					
Intercept (γ_{20})	11.07	1.29	8.55	398	.000
Self-concept slope					
Intercept (γ_{30})	12.85	1.26	10.20	283	.000
ESCS slope					
Intercept (γ_{40})	7.97	1.32	5.99	255	.000

Random effects	Variance component	*SD*	χ^2	*df*	*p*
Intercept (u_0j)	1,390.25	37.28	1,932.87	210	.000
Student-level effect (*r*)	3,414.91	58.44			

Note. Proportion of variance explained in intercept (β_0) = 0.63.

The student-level model for mathematics achievement in New Zealand (Table 42) paints a slightly more complex picture than previously uncovered. This final model shows the same pattern of negative impact for a unit increase in immigrant status and positive impact for unit increases in self-efficacy, self-concept and ESCS. Specifically, for science self-efficacy and science self-concept, a one unit increase in these values respectively predicts a 24.76 and 12.71 point increase. A one unit increase in ESCS translates to a predicted increase of 17.91 units in mathematics literacy. These results are interpreted singularly with all other variables held constant.

At the school-level model, the estimated science intercept of 525.22 was positively influenced by 45.50 points for school ESCS and negatively 27.30 points by proportion of immigrants in the school. That is, as schools mean ESCS score increased by one unit the mathematics achievement score for a student in that school would increase, on average, by 45.50

units; but as proportion of immigrants in the school increased by one unit, the mathematics achievement would decrease by 27.30 units. The student science self-concept slope (a positive value of 12.71) was further steeped 12.60 unit by an increase in school mean ESCS. Finally, the ESCS slope in influenced by proportion of immigrants. The slope of 17.91 for ESCS would increase with a 100% increase in the proportion of immigrants in a school by 18.20 units. There was significant school variation in average school scores after controlling for students' ESCS and proportion of immigrants in the school. For New Zealand, 44% of the variation in mean achievement for mathematics has been explained by the addition of School ESCS.

Table 42

Final Model for Mathematics Literacy for New Zealand

Variables	Parameters estimate				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed effects					
Science intercept (γ_{00})	525.22	3.49	150.30	133	.000
School ESCS (γ_{01})	45.50	5.28	8.60	167	.000
Proportion immigrant (γ_{02})	-27.30	11.56	-2.30	167	.018
Self-efficacy slope					
Intercept (γ_{20})	24.76	1.44	17.15	2559	.000
Self-concept slope					
Intercept (γ_{30})	12.71	1.78	7.13	864	.000
School ESCS (γ_{31})	12.60	3.58	3.52	533	.001
ESCS slope					
Intercept (γ_{40})	17.91	2.49	7.16	199	.000
Proportion immigrant (γ_{41})	18.20	7.57	2.40	1168	.012
	Variance				
Random effects	component	*SD*	χ^2	*df*	*p*
Intercept (u_0j)	387.72	19.69	481.15	167	.000
Science self-efficacy slope (u_2j)	22.81	4.77	205.99	169	.027
Student-level effect (*r*)	5,414.48	73.58			

Note. Proportion of variance explained in intercept (β_0) = 0.44.

The student-level model for general mathematics achievement in Spain (Table 43) continues the same trend as for other nations in this study. As student immigrant status increases by one unit, the mathematics achievement assessment score is predicted to decrease by 40.81 points. As science self-efficacy, self-concept and ESCS increases by one unit, students are predicted to score 16.60, 14.39 and 14.34 points higher on the mathematics literacy assessment. These results hold when all other variables are held constant.

For the school-level model, school ESCS significantly influenced the intercept. As school mean ESCS increased by one unit, the school average score on mathematics literacy score increased by 21.14 points with other variables held constant. Further, a school mean ESCS increase of one unit also increased the science self-concept slope by 5.08 points. There was significant school variation in average school scores after controlling for school ESCS. The science self-efficacy slope, science self-concept slope and the ESCS slope varied significantly across schools. The variation in mathematics mean achievement for Spain that has been explained by School ESCS is 20%. Additionally, the residual variance on science self-concept slope is reduced by 13% when conditioned for School ESCS.

Table 43

Final Model for Mathematics Literacy for Spain

Variables	Parameters estimate				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed effects					
Science intercept (γ_{00})	496.68	2.11	234.80	661	.000
School ESCS (γ_{01})	22.14	3.01	7.35	684	.016
Immigrant slope					
Intercept (γ_{10})	-40.81	4.77	-8.50	685	.000
Self-efficacy slope					
Intercept (γ_{20})	16.60	1.15	14.72	168	.000
Self-concept slope					
Intercept (γ_{30})	14.39	1.23	11.6	427	.000
School ESCS (γ_{31})	5.08	1.77	2.86	172	.005
ESCS slope					
Intercept (γ_{40})	14.34	1.08	13.28	685	.000

Random effects	Variance component	*SD*	χ^2	*df*	*p*
Intercept (u_0j)	597.34	24.44	1,308.24	335	.000
Immigration slope (u_1j)	1,734.22	41.63	633.39	336	.000
Science self-efficacy slope (u_2j)	38.65	6.21	494.27	336	.000
Science self-concept slope (u_3j)	76.00	8.1	581.89	335	.000
ESCS slope (u_4j)	22.89	4.78	503.98	336	.000
Student-level effect (*r*)	4,985.11	70.61			

Note. Proportion of variance explained in intercept (β_0) = 0.20; self-concept slope (β_3) = 0.13.

The student-level model for mathematics achievement in the United States is presented Table 44. This final model shows a familiar pattern of positive impact for unit increases in science self-efficacy, science self-concept and ESCS. Specifically, the mathematics conditioned mean of 459.54 is impacted by a one unit increase in either science self-efficacy and science self-concept, by a predicted value of 13.10 and 10.04 point increase respectively. A one unit increase in ESCS translates to a predicted increase of 20.51 units in science literacy. These results are interpreted singularly with all other variables held constant.

At the school-level model, School level ESCS was found to significantly influence the prediction of science achievement. The conditioned science intercept of 459.54 was positively influenced by 50.19 points for a one point shift in school ESCS. The student science self-efficacy slope (a positive value of 13.10) increased by 8.76 units for every unit increase in school mean ESCS. There was significant school variation in average school scores after controlling for students' ESCS. For the United States, 39% of the variation in mean achievement for mathematics has been explained by the addition of School ESCS.

Table 44

Final Model for Mathematics Literacy for the United States

Variables	Parameters estimate

	Coefficient	*SE*	*t*	*df*	*p*
Fixed effects					
Science intercept (γ_{00})	459.54	3.68	124.57	164	.000
School ESCS (γ_{01})	50.19	8.54	5.87	164	.000
Self-efficacy slope					
Intercept (γ_{20})	13.10	1.43	9.13	49	.000
School ESCS (γ_{21})	8.76	2.09	4.19	161	.000
Self-concept slope					
Intercept (γ_{30})	10.04	1.35	7.43	68	.000
ESCS slope					
Intercept (γ_{40})	20.51	1.47	13.90	1324	.000

Random effects	Variance component	*SD*	χ^2	*df*	*p*
Intercept (u_0j)	75.49	31.23	1,252.96	164	.000
Student-level effect (*r*)	4,711.08	68.63			

Note. Proportion of variance explained in intercept (β_0) = 0.39.

Reading literacy. This final model for reading literacy in Australia (Table 45) indicates that students who are native to Australia, have higher reported scores for self-efficacy and self-concept and who come from homes with higher socioeconomic status will attain higher science literacy scores on PISA. Specifically, as the value of immigrant status increases by one unit, reading achievement score is predicted to decrease by 9.24 points, and for self-efficacy and self-concept, a one unit increase predicts almost 22 and 15 points respectively. A one using increase in ESCS translates to a predicted increase of 16.11 units in reading literacy. These results are interpreted singularly with all other variables held constant.

Additionally, at the school level, attending a school with a one unit greater mean ESCS will increase the intercept value (originally 504.14) by just over 49 units (almost half a standard deviation). These results continue to be interpreted individually with all other variables held

constant. There was significant school variation in average school scores after controlling for school ESCS. The immigrant slope, science self-efficacy slope, science self-concept slope and the ESCS slope all varied significantly across schools. For the Australia, 39% of the variation in mean achievement for reading has been explained by the addition of School ESCS.

Table 45

Final Model for Reading Literacy for Australia

Variables	Parameters estimate				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed effects					
Science intercept (γ_{00})	504.14	1.93	261.19	353	.000
School ESCS (γ_{01})	49.05	4.69	10.53	353	.000
Immigrant slope					
Intercept (γ_{10})	-9.24	2.48	-3.72	354	.000
Self-efficacy slope					
Intercept (γ_{20})	21.66	1.08	20.01	109	.000
Self-concept slope					
Intercept (γ_{30})	14.64	1.15	12.69	124	.000
ESCS slope					
Intercept (γ_{40})	16.11	1.53	10.46	93	.000
	Variance				
Random effects	Component	*SD*	χ^2	*df*	*p*
Intercept (u_0j)	528.11	22.98	832.27	305	.000
Immigration slope (u_1j)	288.72	16.99	398.58	306	.000
Science self-efficacy slope (u_2j)	39.16	6.25	372.56	306	.006
Science self-concept slope (u_3j)	46.10	6.78	365.01	306	.011
ESCS slope (u_4j)	91.06	9.54	405.08	306	.000
Student-level effect (r)	5,311.94	72.88			

Note. Proportion of variance explained in intercept (β_0) = 0.39.

Table 46 shows that for reading literacy in Canada, at the student-level model, students who are native, have higher reported scores for self-efficacy and self-concept and who come from homes with higher socioeconomic status will attain greater achievement scores. Specifically, as the value of immigrant status increases by one unit, the reading literacy score is predicted to decrease by 18.19 points, and for science self-efficacy and science self-concept, a one unit increase predicts a 20.53 and 12.89 point increase respectively. A one unit increase in ESCS translates to a predicted increase of 14.81 units in reading literacy. These results are interpreted in isolation with all other variables held constant.

Table 46

Final Model for Reading Literacy for Canada

Variables	Parameters estimate				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed effects					
Science intercept (γ_{00})	504.21	3.30	152.49	893	.000
School ESCS (γ_{01})	48.21	6.51	7.39	893	.000
Immigrant slope					
Intercept (γ_{10})	-18.19	3.79	-4.79	35	.000
Self-efficacy slope					
Intercept (γ_{20})	20.53	1.24	16.57	894	.000
Self-concept slope					
Intercept (γ_{30})	12.89	1.18	10.89	894	.000
ESCS slope					
Intercept (γ_{40})	14.81	1.51	9.78	155	.000
	Variance				
Random effects	component	*SD*	χ^2	*df*	*p*
Intercept (u_0j)	1,240.77	35.22	1,339.79	463	.000
Immigration slope (u_1j)	1,144.60	33.83	757.69	464	.000

Science self-efficacy slope (u_2j)	92.24	9.60	775.78	464	.000
Science self-concept slope (u_3j)	99.46	9.97	807.32	464	.000
ESCS slope (u_4j)	54.01	7.34	631.58	464	.004
Student-level effect (r)	5,565.49	74.60			

Note. Proportion of variance explained in intercept (β_0) = 0.20.

At the school-level model, the estimated reading intercept of 504.21 was positively influenced by 48.21 points for school ESCS. That is, as schools mean ESCS score increased by one unit the mathematics achievement score for a student in that school would increase, on average, by 48.21 units. There was significant school variation in average school scores after controlling for students' ESCS and proportion of immigrants in the school. Similar to Australia, the science self-efficacy slope, science self-concept slope and the ESCS slope all varied significantly across schools. Again for Canada the variation in mean achievement for reading has been explained by the addition of School ESCS (i.e., 20%) is relatively consistent.

The student-level model for reading achievement in Germany (Table 47) - intercept 475.04 - indicates a negative impact for immigrant status (-25.32) but positive impacts of science self-efficacy and ESCS (18.31 and 4.01) - science self-concept was not a significant predictor in this country for reading achievement. These changes are based upon single increases in the student level variables and hold true when all other variables remain constant.

For the school-level model, only school ESCS significantly influenced the intercept in the final HLM model. As school mean ESCS increased by one unit, the school average score on reading literacy increased by a sizable 104.30 points with other variables held constant. There was no significant school variation in average school scores after controlling for the student level variables in this model. For Germany, a relatively high value of 64% of the variation in mean achievement for reading has been explained by the addition of School ESCS.

Table 47

Final Model for Reading Literacy for Germany

Variables	Parameters estimate				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed effects					
Science intercept (γ_{00})	475.04	3.57	132.83	210	.000
School ESCS (γ_{01})	104.30	6.50	16.04	210	.000
Immigrant slope					
Intercept (γ_{10})	-25.32	4.41	-5.74	210	.000
Self-efficacy slope					
Intercept (γ_{20})	18.31	1.40	13.04	65	.000
ESCS slope					
Intercept (γ_{40})	4.01	1.63	2.49	54	.017
Random effects	Variance component	*SD*	χ^2	*df*	*p*
Intercept (u_0j)	1,429.66	37.81	1,631.50	210	.000
Student-level effect (*r*)	4,282.30	65.43			

Note. Proportion of variance explained in intercept (β_0) = 0.64.

The student-level model in New Zealand (Table 48) shows a similar pattern to Canada in regards to reading achievement. A unit increases in self-efficacy, self-concept and ESCS translates into positive gains. Specifically, as the value science self-efficacy and science self-concept increase one unit, this model predicts a 31.49 and 7.09 point increase respectively. A one using increase in ESCS translates to a predicted increase of 22.68 units in science literacy. These results are interpreted singularly with all other variables held constant.

At the school-level model, school ESCS was found to be significant. The estimated reading intercept of 518.24 was positively influenced by 35.84 points for school ESCS. That is, as schools mean ESCS score increased by one unit the reading achievement score for a student in

that school would increase, on average, by 35.84 units. Finally, the ESCS slope (22.68) is influenced by the school mean proportion immigrants (22.93). What these numbers indicate is that the student level slope for ESCS is made greater for a 100% increase in the school proportion of immigrants. There was significant school variation in average school scores after controlling for students' ESCS. The science self-concept slopes also varied between schools in this model. The variation in reading mean achievement for New Zealand that has been explained by School ESCS is 18%.

Table 48

Final Model for Reading Literacy for New Zealand

Variables	Parameters estimate				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed effects					
Science intercept (γ_{00})	518.24	3.14	164.62	168	.000
School ESCS (γ_{01})	35.84	6.74	5.31	168	.000
Self-efficacy slope					
Intercept (γ_{20})	31.49	1.83	17.19	206	.000
Self-concept slope					
Intercept (γ_{30})	7.09	2.00	3.53	169	.007
ESCS slope					
Intercept (γ_{40})	22.68	2.84	7.91	215	.000
Proportion immigrant (γ_{41})	23.93	772	3.09	536	.004
	Variance				
Random effects	component	*SD*	χ^2	*df*	*p*
Intercept (u_0j)	1,008.13	31.75	685.54	167	.000
Science self-concept slope (u_3j)	63.88	7.99	209.75	168	.016

Student-level effect (*r*)	6,647.89	81.89

Note. Proportion of variance explained in intercept (β_0) = 0.18.

The final model in this study is for reading literacy achievement in Spain (Table 49) and shows that students who are native, have higher science self-efficacy, science self-concept and socioeconomic status are predicted to score higher in reading literacy than students who have lower levels of these variables. Specifically, as the immigrant status increases, reading literacy achievement score is predicted to decrease by 31.28 points. An increase in the self-reported science self-efficacy and self-concept measures of one unit, predicted reading literacy achievement to increase by 18.76 and 3.48 points. Lastly, a one unit increase in ESCS predicts an increase of 11.40 points on the reading literacy assessment. These results hold when all other variables are held constant.

Table 49

Final Model for Reading Literacy for Spain

Variables	Parameters estimate				
	Coefficient	*SE*	*t*	*df*	*p*
Fixed effects					
Science intercept (γ_{00})	478.26	2.55	187.39	684	.000
School ESCS (γ_{01})	22.43	3.58	6.26	684	.000
Immigrant slope					
Intercept (γ_{10})	-31.28	5.15	-6.06	685	.000
Self-efficacy slope					
Intercept (γ_{20})	18.76	1.18	15.81	685	.000
Self-concept slope					
Intercept (γ_{30})	3.48	1.19	2.91	685	.004
ESCS slope					
Intercept (γ_{40})	11.40	1.24	9.15	253	.000

Random effects	Variance component	*SD*	χ^2	*df*	*p*
Intercept (u_0j)	781.19	27.94	1,603.42	335	.000
Immigration slope (u_1j)	1,862.00	43.15	613.41	336	.000
Science self-efficacy slope (u_2j)	67.76	8.23	552.14	336	.000
Science self-concept slope (u_3j)	77.19	8.78	615.23	336	.000
ESCS slope (u_4j)	32.34	5.69	449.06	335	.000
Student-level effect (*r*)	5,031.37	70.93			

Note. Proportion of variance explained in intercept (β_0) = 0.17.

For the school-level model, an increase of one unit in school ESCS, positively impacted the school average score on the reading literacy assessment by 22.43 points. There was significant school variation in average school scores after controlling for school ESCS. For Spain, 17% of the variation in mean achievement for reading is explained by the addition of School ESCS.

Final Model Comparison

Overall, the first overall observation seen among these six nations (i.e., Australia, Canada, Germany, New Zealand, Spain and the United States) lies in the proportion of variance in students' achievement attributable to schools (Table 31). The proportion of students' achievement variance attributed to schools in almost all the countries (with the exception of Germany) ranged from .16 to .29. Germanys' intracalss correlation values ranged from .57 to .68. These findings suggest that the effects of school characteristics on students' achievement are homogenous and in the neighborhood of 20% for all the countries in this study other than Germany. Table 33 further emphasizes this point by detailing the impact on variance reduction at the student level by the addition of the student level variables of science self-efficacy, science self-concept, ESCS and immigrant status across all domains and all nations. Again, for all nations other than Germany, this reduction represents a range from a low of .20 for mathematics in Germany to a high of .37

for mathematics in New Zealand. By comparison, Germany reduced the student level variance by .22, .17 and .08 for science, mathematics and reading by adding these same variables.

Tables 32 through 48 summarize the final models for all nations in this study and indicate the significant variables in both Level 1 and Level 2 (these models are further represented in Appendix I). There are many striking similarities among the final models for all countries. At Level 1, for almost all countries across all domains, immigrant status, science self-efficacy and self-concept as well as ESCS had significant predictive influence on one of the literacy domains (the exceptions being, immigrant status for Australia and the United States for mathematics literacy, New Zealand and immigrant status for both mathematics and reading and science self-efficacy in Germany for reading). Immigrant status tended to negatively influence achievement (i.e., non-native students are predicted to have lower performance) in the range of one-half a standard deviation, while science self-efficacy and science self-concept positively influenced achievement at close to half that of immigrant status for a relative increase of one unit. Finally, the student level ESCS variable impacted achievement positively but not quite to the level of either of the science self-belief measures.

At the school level of the models (level 2), school mean ESCS or school proportion of immigrants were found to significantly influence the level 1 predictors. On the intercept, school mean ESCS was found to consistently influence achievement for all nations. So consistently, that only one nation in one domain (New Zealand and mathematics achievement) added the influence of proportion of immigrants to the model; which in this case, negatively influenced the intercept.

However, the intercept aside, a good deal of variability across nations was observed at level 2. Proportion of immigrants at the school level for Australia and science literacy was only once significant predicator for the student level immigrant slope coefficient. Similarly, the

science self-efficacy slope was only once significantly influenced by the school level predictor of school ESCS. This time the country and domain influenced was the United States and mathematics (a positive influence and slope increase). The science self-concept slope was consistently (8 out of 17 times) and positively related to school mean ESCS. A pattern for science self-concept and the influence for school ESCS did not appear among the countries in the study; however, between domains it only influenced significantly in science and mathematics but not in reading literacy. Finally, the slope for student level ESCS, when significantly influenced was so by either school ESCS, proportion of immigrants or both. However, interestingly both of these school level predictors made the slope of ESCS steeper. That is, with their addition the impact of ESCS on achievement was stronger. No apparent pattern was observed for these variables at level two.

Table 50

Final Models Overview for Science Literacy for PISA 2006

Level	Variable	Australia	Canada	Germany	New Zealand	Spain	United States
Student level	Immigrant status	sig. (-)	sig. (-)	sig. (-)	sig. (-)	sig. (-)	sig. (-)
	Science self-efficacy	sig. (+)	sig. (+)	sig. (+)	sig. (+)	sig. (+)	sig. (+)
	Science self-concept	sig. (+)	sig. (+)	sig. (+)	sig. (+)	sig. (+)	sig. (+)
	ESCS	sig. (+)	sig. (+)	sig. (+)	sig. (+)	sig. (+)	sig. (+)
School level	†Intercept	School ESCS (+) sig. error	School ESCS (+) sig. error	School ESCS (+) sig. error	School ESCS (+) sig. error	School ESCS (+) sig. error	School ESCS (+) sig. error
	Immigrant slope	Proportion immigration (-) sig. error	sig. error			sig. error	School ESCS (+) sig. error
	Science self-efficacy slope	sig. error	sig. error		sig. error	sig. error	sig. error
	Science self-concept slope	School ESCS (+) sig. error	sig. error		School ESCS (+) sig. error	School ESCS (+) sig. error	School ESCS (+) sig. error
	ESCS slope	sig. error	sig. error		School ESCS (-) Proportion immigration (+) sig. error	sig. error	

Note. Value in brackets next to each variable indicates the direction of influence on academic achievement score.

† Intercept is the β_{0j}, and represents the influence on average school score.

Sig. represents non-zero value at $p < .05$ and sig. error represents differences across schools on the coefficient.

Table 51

Final Models Overview for Mathematics Literacy for PISA 2006

Level	Variable	Australia	Canada	Germany	New Zealand	Spain	United States
Student level	Immigrant status		sig. (-)	sig. (-)		sig. (-)	
	Science self-efficacy	sig. (+)	sig. (+)	sig. (+)	sig. (+)	sig. (+)	sig. (+)
	Science self-concept	sig. (+)	sig. (+)	sig. (+)	sig. (+)	sig. (+)	sig. (+)
	ESCS	sig. (+)	sig. (+)	sig. (+)	sig. (+)	sig. (+)	sig. (+)
School level	† Intercept	School ESCS (+) sig. error	School ESCS (+) sig. error	School ESCS (+) sig. error	School ESCS (+) Proportion immigration (-) sig. error	School ESCS (+) sig. error	School ESCS (+) sig. error
	Immigrant slope		sig. error			sig. error	
	Science self-efficacy slope	sig. error	sig. error			sig. error	School ESCS (+)
	Science self-concept slope	School ESCS (+) sig. error	sig. error		School ESCS (+) sig. error	School ESCS (+) sig. error	
	ESCS slope	sig. error	sig. error		Proportion immigration (+) sig. error	sig. error	

Note. Value in brackets next to each variable indicates the direction of influence on academic achievement score.

† Intercept is the β_{0j}, and represents the influence on average school score.

Sig. represents non-zero value at $p < .05$ and sig. error represents differences across schools on the coefficient.

Table 52

Final Models Overview for Reading Literacy for PISA 2006

Level	Variable	Australia	Canada	Germany	New	Spain	United

					Zealand		States
Student level	Immigrant status	sig. (-)	sig. (-)	sig. (-)		sig. (-)	na
	Science self-efficacy	sig. (+)	sig. (+)	sig. (+)	sig. (+)	sig. (+)	na
	Science self-concept	sig. (+)	sig. (+)		sig. (+)	sig. (+)	na
	ESCS	sig. (+)	sig. (+)	sig. (+)	sig. (+)	sig. (+)	na
School level	† Intercept	School ESCS (+) sig. error	School ESCS (+) sig. error	School ESCS (+) sig. error	School ESCS (+) sig. error	School ESCS (+) sig. error	na
	Immigrant slope	sig. error	sig. error			sig. error	na
	Science self-efficacy slope	sig. error	sig. error			sig. error	na
	Science self-concept slope	sig. error	sig. error		sig. error	sig. error	na
	ESCS slope	sig. error	sig. error		Proportion immigration (+) sig. error	sig. error	na

Note. Value in brackets next to each variable indicates the direction of influence on academic achievement score.

† Intercept is the β_{0j}, and represents the influence on average school score.

Sig. represents non-zero value at $p < .05$ and sig. error represents differences across schools on the coefficient.

Chapter 5: Summary, Discussion, and Conclusion

What can we learn from PISA 2006 that will aid researchers, policy makers, and educators in their efforts to improve scientific literacy? More specifically, how can we use information on students' science self-beliefs and SES as well as school-level contextual variables

to foster an increase in scientific literacy for immigrant students to a new country? Sammons (2006) has noted that conducting studies across different contexts can challenge our preconceptions and potentially gain insight into policy and practice. In an effort to isolate some of the academic influences on science literacy, student background variables have been identified and analyzed in isolation and in the larger school context to help answer these broad research questions.

A scientifically literate person is one who can ask, find, or determine answers to questions derived from curiosity about everyday experiences. It also means that a person has the ability to describe, explain, and predict natural phenomena (National Science Education Standards, 1996). It has been claimed that scientific literacy should be the outcome of science for all students (Turmo, 2004). However, efforts to define the term in a mutually agreed upon manner and to uncover instructional practices that foster scientific literacy and the achievement of such learning outcomes are daunting tasks. There are some who believe the education system is failing in this charge and that most of us no longer have any idea of what is scientifically plausible and what is scientific nonsense (Homer-Dixon, 2001). Scientific literacy has been linked to a more productive workforce (Hanushek et al., 2008; McEneaney, 2003), a population better prepared to participate effectively in public discourse (DeBoor, 2000), and helping individuals lead personally fulfilling and responsible lives (Laugksch, 1999).

In this study, the relationships between science self-beliefs and science literacy (as defined by PISA) across all nations that participated in PISA 2006 were explored. Subsequently, the relationships between these same science self-beliefs, socio-economic and immigrant status, and science literacy for countries of high immigration were examined.

First, determining international comparisons of science self-efficacy and science self-concept with science achievement is useful in uncovering cultural differences that influence students' view of self as it relates to achievement. Additionally, because the underlying causes of racial/ethnic gaps in achievement across many countries are so poorly understood (Rangvid, 2007), these findings can provide possible interventions for policy makers and educators.

In a second exploration in this study, SES—regarded as one of the strongest predictors of achievement at school (Turmo, 2004)—was investigated for the three sub-constructs that constitute the PISA variable economic, social, and cultural capital (ESCS). Because a student's families can posses differing amounts of these three constructs, an exploration of the relative importance of each one in the composite index was undertaken here. Tyson et al. (1996) has proposed a three-lens, multi-perspective instructional approach to scientific literacy. Of these three lenses, the ontological one examines the way students view the nature of the construct being studied in the science classroom. The foundation for this ontological view can be linked to students' previous experiences and backgrounds and is theorized to influence science learning. By identifying the relative importance of these three sub-constructs in ESCS, there is potential here to influence a student's ontological view of the world to improve scientific literacy.

Finally, the relationships among science self-beliefs, immigrant status, SES, and academic achievement were examined for six nations in PISA that are currently preferred destinations for international migration (i.e., Spain, Germany, Canada, the United States, Australia, and New Zealand). Exploring how science self-beliefs, levels of SES, and immigrant status predict academic achievement is of interest in our highly nomadic world. These nations have been experiencing increasing immigration in the past half century that is projected to continue to 2050 (UN, 2006). Uncovering areas for potential exploration in better understanding

educational environments suitable for these new or recent arrivals is helpful to both the educational system and the larger society in which it is housed.

The primary aim of this study was to (a) explore correlations among science self-concept, science self-efficacy, and science achievement for students in the participating nations of PISA 2006, (b) determine how much of the variance cultural, social, and economic capital (the elements of the SES variable in PISA) accounts for when predicting scientific literacy, (c) determine the model between scientific literacy and science self-concept, science self-efficacy, SES, and immigrant status as defined by PISA for students in Spain, Germany, Canada, the United States, Australia, and New Zealand, and (d) suggest ways that countries might improve students' science achievement according to the findings in this study. The data for this analysis was taken from the OECD's PISA 2006 survey.

Summary of Findings

The analyses carried out for this study were focused in two areas: (a) science self-beliefs and science achievement and (b) linear and multilevel regression for these same science self-beliefs, SES, and immigrant status. In this section, the findings are briefly summarized according to research question with a more detailed discussion to follow. Most of the variables in this study are complex and composed of several items on the student questionnaire. Thus, to avoid simplistic and potentially inappropriate policy or practice implications, the suggestions made by Ma and Klinger (2000) will be followed, and recommendations will be tied specifically to the measurement of associated variables. For example, because the variable ESCS in PISA is linked to family attitudes and beliefs about school instead of income, findings may suggest opportunities to work with parents and students to improve academic achievement according to the social construct of ESCS more so than according to a financial one.

Relationships Among Science Self-concept, Science Self-efficacy, and Science Literacy

The first research question focused on science self-beliefs and science achievement. All countries that participated in PISA 2006 were ranked by both average science self-efficacy and science self-concept compared to achievement. This ranking uncovered a statistically significant mean difference for science self-concept and science literacy, $t(54) = -7.22$, $p < .05$, when the countries were median split. Interestingly, four of the five nations that ranked lowest on self-concept and high scoring on achievement were Asian. This supports the geographical findings uncovered by Wilkins (2004) with TIMSS data. A statistically significant mean difference for science self-efficacy and science literacy, $t(36) = 14.9$, $p < .05$ was also uncovered when the rankings were compared between the top and bottom third.

Additionally, at the overall student and aggregated country level, the correlations between science self-efficacy and science achievement were positive ($r = .33$ and .23, respectively) but only the student level correlation was significant. However, for science self-concept and science achievement, the correlation was significant at both levels but only .22 for aggregate student and −.74 for aggregate country. This finding would suggest that, on average, countries with higher science self-concept tend to achieve lower on scientific literacy (and vice versa). These results can be further referenced in Tables 10 and 11.

Variance Accounted for by Cultural, Social, and Economic Capital When Predicting Scientific Literacy?

The next research focus explored the relationship between student scientific literacy and the SES variable according to Coleman's (1988) ideas of cultural, social, and economic capital. To achieve this, multiple regression was employed to determine how much of the variance in scientific literacy could be explained by the combination of the constructs presented in Table 7.

Results demonstrate that 16% of the variance in scientific literacy was explained by cultural capital, 14% by social capital, and 3% for wealth and 9% for home possessions (the highly correlated constructs of economic capital were regressed independently). Finally, the PISA composite variable ESCS was also regressed on scientific literacy with a resulting overall R^2 value of .13 for all nations, indicating that 13% of the variance for scientific literacy was explained by this composite.

Empirical Relationship Between Scientific, Mathematic, and Reading Literacy and Science Self-concept, Science Self-efficacy, SES, and Immigrant Status for Students in Spain, Germany, Canada, the United States, Australia, and New Zealand

Lastly, a series of multilevel models using HLM were run for the nations of Spain, Germany, Canada, the United States, Australia, and New Zealand to examine students' science self-beliefs as well as immigrant and SES status and their relation to academic achievement across all domains of PISA (i.e., science, math, and reading). This section is organized initially by the correlations among and between the literacy domains and student and school-level predictors. Subsequently, the null models are explained and then finally the contextual models of all nations within each literacy domain. It was felt that by presenting the results from this section of the analysis in this manner, a better overall picture of the patterns that emerged from these final models within and between the literacy domains of PISA 2006 could be more clearly depicted.

Correlations. Correlations among the student-level variables and the literacy domains for countries selected in this part of the analysis were more homogeneous. These results can be referenced in Tables 18–23. At the student level, the correlations for the literacy domains were consistently high and significant, in the range of .8, with science and mathematics literacy the

largest. Variables of science self-concept, science self-efficacy, and ESCS and the three literacy measures were moderately correlated (in the range of 0.3–0.4). Science self-concept and science self-efficacy significantly correlated with each other in the 0.5 range and with ESCS at approximately 0.2. Immigrant status tended to correlate with the other student level variables as well as the literacy domains noticeably lower, at less than 0.1, negative, and/or non-significant.

At the school level (see Tables 24–29), school ESCS is positively and highly correlated with the literacy domains (low of .52 in Spain and high of .84 in Germany). However, an inconsistent result in *r* for the proportion of immigrants at the school level and achievement across countries was observed. When school proportion of immigrants is correlated with the literacy domains, a moderate and positive relationship is observed for Australia and Canada ($r \approx .2$). These same correlations for New Zealand were weak and non-significant. However, for Germany, Spain, and the United States, a moderate to strong negative association was uncovered (with a low of −.24 in Spain and a high of −.53 in Germany). This suggests that the migration patterns and school structures may have some similarities within these nations that differ from the traditional nations of immigration (i.e., Canada, Australia and New Zealand). This idea is further explored later in this chapter.

Null models. The null models (Table 31) for the PISA 2006 science, math, and reading results (i.e., the intra-class correlation (ICC) or proportion of student achievement variance attributable to schools) were similar across all domains for Spain, Canada, Australia, New Zealand, and the United States ($p = .16–.29$). However, the ICC was considerably higher in Germany at .57 for science, .61 for math, and .68 for reading. This is not surprising as Germany formally tracks students (Marks, 2005). Because of this, students in Spain, Canada, Australia, New Zealand, and the United States will be more heterogeneous within schools and account for

more variance at the student level. Predictably, Table 32 demonstrates that with the addition of student-level variables, the within-school variance is reduced by approximately 20–30% for Spain, Canada, Australia, New Zealand, and the United States (with Germany lower than the other nations potentially because it had a much smaller proportion of variance to model at the student level).

Contextual models. Information on the final models can be referenced in Tables 32–49 as well as in Appendix I. Here, the models for the six countries analyzed by literacy domain are presented. Overall, conditioned means (see Table 10) were split into two groups with Australia, Canada, and New Zealand (range of 510.99–531.90) consistently above the OECD average (i.e., mean of 500, standard deviation of 100) compared to Germany, Spain, and the United States (range of 473.85–495.64) consistently below. One exception to this observed pattern was Germany, and its results for science literacy were slightly above the mean (i.e., 507.17).

Science literacy. In the final model for science literacy in Australia, immigrant status, science self-efficacy, science self-concept, and student ESCS significantly predicted achievement at the student level. On the intercept, school-level ESCS was significant at level 2, and there was significant variability observed across schools. Specifically, as the value of immigrant status increases by one unit, science literacy score is predicted to decrease by 23 points with all other variables held constant. For self-efficacy and self-concept, a one-unit increase predicts a 26.42 and 21.34 point increase respectively. A one-unit increase in ESCS translates to a predicted increase of 14.99 units in science literacy. These results are interpreted singularly with all other variables held constant.

Additionally, at the school level, attending a school with a one-unit greater mean ESCS will increase the predicted school mean score (originally 519.99) by almost 49 units (half a

standard deviation). The student immigrant slope is also made steeper by attending a school with all immigrant students by 25.67 units. The change would be 2.57 units for a proportional increase of 10%. Finally, the self-concept slope is increased by 5.92 units as the school mean ESCS increases by one unit. The immigrant slope, science self-efficacy slope, science self-concept slope, and the ESCS slope all varied significantly across schools. Again, these results are interpreted individually with all other variables held constant.

Each of the five other nations included in this section of the analysis (i.e., Canada, Germany, New Zealand, Spain, and the United States) showed the same significant predictors at the student level (see p. 156) as well as relative size and direction of influence on the conditioned mean (e.g., immigrant status negatively influenced the conditioned mean, while science self-efficacy, science self-concept, and ESCS positively influenced the conditioned mean). Additionally, school-level ESCS was also significant at level 2 on the intercept with significant variability across schools for all six nations. However, variability in the models was observed at the school level.

For Canada, at the school level, there were no significant contributions made by either school ESCS or school proportion of immigrants on the slopes for immigrant status, science self-concept, science-self efficacy, or ESCS. However, the immigrant slope, science self-efficacy slope, science self-concept slope, and the ESCS slope all varied significantly across schools. For Germany, at the school level, there also were no significant contributions made by either school ESCS or school proportion of immigrants on the student level slopes. However, unlike Canada, the immigrant slope, science self-efficacy slope, science self-concept slope, and the ESCS slope did not vary significantly across schools.

In New Zealand, there was a significant influence on the science self-concept slope for

school ESCS (14.22) and additional significant influence of both school ESCS (−11.65) and proportion of immigrants (26.39) on the ESCS slope. Only the science self-efficacy slope and science self-concept slope varied significantly across schools. Spain and the United States were very similar for science literacy with school ESCS on science self-concept the only significant influence at the school level (3.67 and 13.03 respectively). For both countries, the immigrant slope, science self-efficacy slope, and science self-concept slope all varied significantly across schools. However, the ESCS slope only varied across schools for Spain.

Mathematics literacy. For mathematics literacy, the six countries can be divided according to the student-level significant predictors. In the first group (i.e., Canada, Germany, and Spain), immigrant status, science self-efficacy, science self-concept, and student ESCS significantly predicted achievement at the student level. For the second group (i.e., Australia, New Zealand, and the United States), only science self-efficacy, science self-concept, and student ESCS significantly predicted achievement at the student level. The pattern that emerged across all nations was a negative influence for immigrant status (for those in the first group) and a positive one for science self-efficacy, science self-concept, and student ESCS. This is the same pattern observed previously for science literacy. Additionally, on the intercept, school-level ESCS was significant at level 2 for all nations (with a sizable range of 100 in Germany and 22 in Spain), and there was significant variability observed across schools. The only addition on the intercept was for New Zealand, which also added the significant contribution of school proportion of immigrants. In this case, attending a school in New Zealand with all immigrants decreased the conditioned intercept 27 points.

The school-level models again show much variability, and discussion will continue with the previously identified groups. In the first group, Canada and Germany had no significant

predictors at the school level outside of the intercept. However, for Canada, the immigrant slope, science self-efficacy slope, science self-concept slope, and the ESCS slope all varied significantly across schools. For Germany, none did. Spain added the school-level predictor of school ESCS for the science self-concept slope (5.08). Like Canada, the immigrant slope, science self-efficacy slope, science self-concept slope, and ESCS slope all varied significantly across schools.

In the second group, Australia demonstrated a significant influence of school ESCS (6.21) on the science self-concept slope. Only the science self-efficacy slope and science self-concept slope varied significantly across schools. For the United States, a significant influence of school ESCS (8.76) on the science self-efficacy slope was modeled. Additionally, none of the slopes for student-level variables varied significantly across schools. Finally, New Zealand added the significant contribution of school ESCS on the science self-concept slope (12.6) and proportion of immigrants on the ESCS slope (18.2). Like the United States, none of the student-level slopes varied significantly across schools.

Reading literacy. For reading literacy, Australia, Canada, and Spain had similar models. All three showed immigrant status, science self-efficacy, science self-concept, and student ESCS significantly predicting achievement at the student level. These variables were again found to negatively influence the slope for immigrant status and positively influence the conditioned mean for science self-efficacy, science self-concept, and student ESCS. Germany modeled the significant student level predictors to immigrant status (−25.32), science self-efficacy (18.31), and student ESCS (4.01), while New Zealand modeled the significant predictors of science self-efficacy (31.49), science self-concept (7.09), and student ESCS (22.68).

Maintaining the trend seen for the other literacy domains, school-level ESCS was

significant and positive predictor on the intercept at level 2 for all nations. In this case, the values of school ESCS on the intercept The coefficients were 49.05 for Australia, 48.21 for Canada, 104.30 for Germany, 35.84 for New Zealand, and 22.43 for Spain. There was significant variability observed across schools on the intercept for all countries after conditioning on ESCS.

For the four countries of Australia, Canada, Spain, and Germany, no school-level predictors outside of the intercept were found. Additionally, for Canada, Australia, and Spain, the immigrant slope, science self-efficacy slope, science self-concept slope, and the ESCS slope all varied significantly across schools. For Germany, none of the student-level slopes for immigrant status, science self-efficacy, and ESCS did. In New Zealand, the proportion of immigrant students in a school significantly influenced the student-level ESCS slope by close to 24 units. Additionally, only the slope for science self-concept varied across schools significantly. Data for the United States was not provided in PISA 2006 for reading literacy.

Findings

Potentially meaningful findings within the areas of focus in this study have been uncovered here. First, within country those students with higher science self-efficacy and science self-concept tend to have higher achievement. However, at the national level, student populations with higher science self-concept tend to achieve lower on scientific literacy (and vice versa). This finding has been uncovered previously in analysis of TIMSS (Wilkins, 2004) and is of interest here as overconfidence may reduce students' incentives to learn and further lead to less effort being applied to their studies (Leung, 2002). Second, the variables that make up the cultural and social capital constructs account for more variance in scientific literacy on their own than does the PISA composite ESCS. This might provide avenues for student and family support that are outside the areas of wealth yet can have positive influence on scientific literacy. Finally,

there is a good degree of homogeneity for final models across the nations selected in this study, which potentially lend themselves to more universal recommendations.

Discussion

An exploration of each of the above findings is discussed in the following section.

Science Literacy and Science Self-efficacy/Science Self-concept

Overall, students who participated in PISA 2006 reported generally positive views about their science self-efficacy and science self-concept. Science self-efficacy and self-concept were measured with a mean of 0 and standard deviation of 1, so positive means a greater valence of response in relation to the nations of the OECD. Considering science self-efficacy first, on average and at the student level, higher science self-efficacy was related to higher achievement. Schunk and Meece (2006) report on studies at the student level across different academic domains with children and adolescents that have demonstrated significant and positive correlations with self-efficacy. This was further supported by within-country analysis. A statistically significant positive correlation between science self-efficacy and science literacy for all 57 nations in PISA 2006 was uncovered. The countries that ranked in the top third on science self-efficacy did perform statistically better in the science literacy domain than those in the lower third ($t(54) = 14.9$, $p < .05$).

The overall positive relationship between science self-efficacy and science achievement was an unsurprising result, as much research supports the hypothesized relationship that self-efficacy influences academic achievement (Schunk & Meece, 2006). Students obtain information to appraise their self-efficacy from—among other things—their actual performance (Pajares & Schunk, 2002). Thus, students who indicated high self-efficacy for science demonstrated significantly higher science achievement than did students with lower science self-efficacy.

With science self-concept, again findings suggest that at the student level, students with higher science self-concept tend to achieve higher academically. A statistically significant positive correlation between science self-concept and science literacy for 48 of the 57 nations in PISA 2006 was uncovered for the within-country analysis. Exceptions included Kyrgyzstan, which was significant but negatively correlated; Thailand, which was non-significant and negatively correlated; and Argentina, Azerbaijan, Brazil, Columbia, Montenegro, Romania, and Indonesia, which were positively correlated but non-significant. However, countries that ranked higher on science self-concept tended to perform less well on science achievement than the group of countries with lower science self-concept. Columbia, Jordan, Thailand, Kyrgyzstan, and Azerbaijan were included in the top five nations in terms of science self-concept, and Japan, Hong Kong—China, the Netherlands, Chinese Taipei, and Korea completed the list of the bottom five in terms of science self-concept but were among the highest scoring nations on science literacy.

At the country level, the negative and significant correlation between science self-concept and science literacy suggests that, on average, countries with higher science self-concept tend to achieve lower on scientific literacy (and vice versa). From the questionnaire data, there appears to be a lack of confidence in doing mathematics in students from countries that achieved the highest (primarily East Asian). What might be observed here at the student and country level is the result of the affective component of self-concept. Because self-concept includes feelings of self-worth and general beliefs in competence (Zimmerman & Cleary 2006), students in strong academic nations may depress their self-concept while students in weak nations may inflate theirs. Leung (2002) has suggested that educational and cultural experiences for students from East Asian nations, such as highly competitive examinations that classify large numbers of

students as failures and cultural expectations for students to rate themselves low, may translate to lower confidence.

Findings from this analysis suggest that the relationship between science literacy and both science self-efficacy and science self-concept differs depending upon the level of analysis: student or country level. Similar to White's (1982) and Sirin's (2005) findings for SES and academic achievement, the analyses of science self-efficacy and science self-concept matter if analysis occurs at the student level or country level. Both White and Sirin found a smaller correlation between SES and academic achievement at the student level (i.e., r = .22 and .28) than at the school level (r = .73 and .60).

Interpretation of these results is speculative. Although within most countries science self-efficacy and science self-concept were positively related to science achievement, this does not suggest a causal link. Because self-concept is developed primarily through interaction with and through the appraisals of others (Pajares & Schunk, 2002), it is not too difficult to see why self-concept might be lower for students in nations that posses more students with higher academic skills. Learning environments that inhibit students from rating themselves too highly on how well they think they do in science could motivate them to put in even more effort at their studies, just as overconfidence may lower students' achievement by decreasing their incentive to learn (Leung, 2002). Further research is necessary to understand these differences across nations and how they influence achievement.

Regression Analysis for PISA Components of SES

SES is a topic of great interest to those who study children's development, despite evidence that great variability exists in what children experience within different levels of SES and across different cultures (Bradley & Corwyn, 2002). The magnitude of the relationship

between student literacy and SES background is highly dependent upon the specific measures used (Turmo, 2004); however, income, education, and occupation level together are generally accepted to represent SES better than any measure alone (White, 1982). In this study, Coleman's (1988) ideas of cultural, social, and economic components of SES are presented.

When the variables that comprised each of these elements of capital were regressed on scientific literacy for the PISA sample, results showed that there are differences in how much of the variance in scientific literacy can be explained by each element. Additionally, the composite variable of ESCS was also regressed on scientific literacy for all countries in the PISA 2006 study (Tables 17–21). Overall, these regression equations demonstrated that for all the nations, cultural capital was the most important explanatory construct for scientific literacy. It accounted for 16% of the variance in scientific literacy scores compared to 14% for social capital, 13% for the composite ESCS, and 12% for economic capital. As has been stated, the statistical analyses of covariance like those used in this study do not imply causation, and results need to be carefully interpreted.

From the literature, cultural capital implies that children from high-status backgrounds (e.g., familiarity with high-status cultural activities like literature and the theatre) are at an advantage as they better understand the hidden curriculum that underlies the educational system and are more favorably judged by its gatekeepers (i.e., teachers and administrators) (Turmo, 2004). Turmo further argues that a strong and direct link between parents' cultural background and student performance in many countries would be unsurprising. Similarly, Marks et al. (2006) found that cultural resources played a more important role in SES inequalities in student achievement than material resources in the home. They believed this influence of cultural capital would be more important in the humanities than in science and mathematics, but results here

point to its relative importance in science.

Social capital is defined as the valued outcomes that surface from social relationships and personal networks (Croll, 2004). In education, it is felt that students do better at school if they have a close social network surrounding them where parents, children, and teachers collaborate and know each other intimately (Turmo, 2004). Further to this, there is some belief that social capital is most important for those who have limited economic and cultural capital, and this might account for its relatively high standing across all nations in PISA. Further analysis between OECD and non-OECD nations could answer this question.

On the other hand, the fact that the nations involved in the PISA 2006 measure are representative of the most economically powerful and richest nations on the planet potentially accounts for the relatively small relationship (even smaller when the predictors were regressed independently) between economic capital and scientific literacy. Among the traditional measures of SES, family income has been cited as accounting for the greatest amount of variance (Bradley & Corwyn, 2002). Many of the children who were involved in this study have access to universal, high-quality, and free education as members of their respective societies. Because economic capital is related to parents with more money being able to cover education-related costs for their children (Turmo, 2004), its relatively lower standing here is understandable. Additionally, the relatively low standing for ESCS—the composite variable for SES in PISA—is also potentially explained by this economic capital argument.

Overall, it would appear that students from homes with high cultural and high social capital in countries involved in the PISA 2006 study are better positioned for improved scientific literacy. Because low levels are not the best-case scenario for nations as they move into the next century, efforts to better meet the science education requirements of student from differing

capital backgrounds are important (Turmo, 2004). Attention to cultural and social capital has the potential to positively influence the ontological element of how the student perceives the topic of study proposed by Tyson et al. (1996). By adopting a perspective that acknowledges students' differing experiences and backgrounds, science teaching and learning can potentially become more relevant and meaningful. Results here suggest that differences exist in the amount of variance accounted for in scientific literacy between students of high and low cultural and social capital. Suggestions are further elaborated in the recommendations section of this chapter.

Multilevel Models

In this final section of the analysis, the relationships between selected student-level and school-level variables for the multilevel models are discussed. Here, a contextual model, one that contains student-level variables (e.g., student ESCS) and aggregated school-level variables (e.g., school mean ESCS) was specified for each of the six countries with relatively high levels of immigration. O'Connell and McCoach (2008) suggest that this type of model is important as the impact of an aggregated school composite over and above the student-level influence may locate relatively advantageous or disadvantageous changes.

Exploring how patterns of science self-beliefs, SES, and immigrant status compare among nations of high immigration levels is of increasing interest to researchers and practitioners. In addition to contributing to the understanding of theory, the countries selected in this section of the analysis have been experiencing increasing immigration from many parts of the world (UN, 2006). Recognition of what works, and what does not, for those immigrant students is essential to teachers and other education stakeholders to make sure that education systems are as equitable as possible for all students.

Science self-beliefs. For all students across all countries and in all domains (with the

notable exception of science self-concept in Germany for reading literacy) both science self-efficacy and science self-concept predicted increased achievement scores. A relative increase in science self-efficacy tended to have a larger influence upon achievement than did science self-concept. For example, for scientific and reading literacy across all nations selected, the science self-efficacy coefficient was consistently larger than science self-concept. However, mathematics literacy countered this trend with science self-concept tending to be similar to or slightly larger than science self-efficacy. Interestingly, yet maintaining the overall pattern observed in the data, science self-efficacy was relatively larger and science self-concept relatively smaller for New Zealand.

Initially, the fact that elevated levels of science self-efficacy and science self-concept predict higher achievement is reassuring. Those who are more self-efficacious about being able to manage circumstances are more likely to succeed (Zimmerman & Cleary, 2006), as are those whose perception of the self is reinforced positively by evaluative inference (Bong & Clark, 1999). The strong and positive correlations between science self-concept and science self-efficacy for all countries across all literacy domains support this finding, as does literature that recognizes making distinctions between these two constructs as difficult (Bong & Shaalvik, 2003).

Although the outcomes of scientific literacy, mathamatics literacy, and reading literacy were highly correlated, the strongest correlations uncovered were between science and math (see Tables 18–23). However, the highest and most consistent findings for the models of science self-efficacy and science self-concept within this study were between science literacy and reading literacy. When the correlations between science self-efficacy and science self-concept and all the literacy domains are explored, some potentially helpful trends emerge. For science self-efficacy,

the correlations are highest for science literacy ($r \approx .5$) and similar between reading and mathematics at .4. For science self-concept, the correlations are highest and similar for mathematics and science ($r \approx .4$) with reading again being lower ($r \approx .3$).

Trying to sort out these conflicting results is difficult and made more so by the fact that self-concept definitions in the literature vary widely (Bong & Clark, 1999). However, one possible resolution to these findings that emerges from the analysis and literature is the level of measurement at which these two science self-beliefs are typically captured and the original definition of scientific literacy in PISA. Self-efficacy is traditionally measured at the specific task level while self-concept is usually tapped higher at the subject level (Bong & Clark, 1999). Thus, the science, mathematics, and reading tasks associated with self-efficacy should be more similar in PISA than the subject-level comparisons associated with self-concept.

The findings of consistent correlations among all the literacy domains and science self-efficacy might support the concept that PISA assesses the fundamental literacy aspect of each domain, because self-efficacy measures how well students believe they can accomplish a disciplinary task (Zimmerman & Cleary, 2006). In this case, the task being assessed for self-efficacy is the fundamental literacy one (i.e., other things allowed reading and writing across all domains), considered important yet missing from many definitions of scientific literacy (Norris & Philips, 2003; Yore et al., 2007). The consistent correlations and slopes across domains for self-efficacy would support such a contention. Additionally, the subject similarity between science and mathematics—compared to reading—also supports the higher correlations for these two domains when self-concept is reported.

Additionally, a slightly closer look at self-efficacy theory and self-concept beliefs might lead one to recognize that both of the variables measured here should be related to science only.

Pajares and Schunk (2002) suggest that how a student sees themselves in dissimilar academic areas can be quite different. Another exploration of the relevant literature uncovers that self-concept is theorized to compile a diverse set of self-perceptions that come into play when determining one's self-concept (Bong & Clark, 2003). Similarly, Bong (1997) uncovered evidence through confirmatory factor analysis for differing self-efficacy factors across specific high school academic subjects. Thus, it appears that both self-efficacy and self-concept are highly differentiated constructs. Despite the differentiated nature of these constructs, there appears to be some support for the contention that considerable overlap in academic self-concept and academic self-efficacy exists and that the perception of academic capability is the major similarity between the two (Bong & Clark, 2003). Perhaps PISA is measuring a more general academic capability than the specific science self-concept and science self-efficacy it reports?

Another potential question about the data is why the coefficients for science self-efficacy and science self-concept are so close in value for the domain of mathematics literacy in Australia, Canada, and Germany. For some reason, these countries across this domain have contrary findings to other nations within that domain and all countries within the other two domains. A final area that needs further exploration is why New Zealand has such higher—yet consistent within the overall pattern—results on these measures. A further exploration of the education system in New Zealand with particular attention to science self-efficacy and science self-concept seems warranted.

Immigrant status. Levels of adaptation among immigrants are generally evaluated by educational attainment (Zhou, 1997). Successful integration of immigrant students into the education system is a current and growing concern for many nations around the world (Dronkers & Levels, 2007). For example, Kao and Thompson (2003) comment that understanding race,

ethnic, and immigrant variation in educational attainment is more important than ever as the U.S. population becomes increasingly diverse. Immigrant status was a significant predictor for all nations selected for this part of the study in scientific literacy, almost all nations for reading literacy (except New Zealand), and half of the nations (Canada, Germany, and Spain) for mathematics.

The generally negative—but varied—influence on the intercept of immigrant student status for nations selected in this study is generally in line with the previous research on PISA. Schleicher (2008) found with PISA 2003 (mathematics focus) that despite strong learning dispositions, immigrant students often perform at levels significantly lower than their native peers. His finding, that these differences are most pronounced in European counties and less so in traditional settlement countries (i.e., Australia, New Zealand, and Canada), is also supported across this study. Interestingly, and a potential follow-up exploration, is that for PISA 2003, in some nations (i.e., Canada and Hong Kong—China), second-generation students performed significantly better than first-generation students (Schleicher, 2006). Potential explanations for this observation include the composition of these immigrant groups as well as integration and education policies directed at aiding these students as they entered the country.

The reasons offered for the generally lower test scores of immigrants are interesting and germane to this conversation. Dronkers and Levels (2007) suggest that it could be the effects of early school segregation in originating countries, further segregation in destination countries, and the reality that schools with many immigrants in destination countries are often ones with less material and educational resources. Immigrants in Germany, for example, self-select into certain primary schools (ones that scored one-half a standard deviation below German students on PISA 2000), which then offer a lower probability of attending the upper secondary schools

(Ammermueler, 2007). However, Rangvid (2007) observed that the substantial gap from PISA 2000 (reading focus) between immigrants and native students in the Copenhagen school system was due to lower expectation and less encouragement from teachers and not contextual school-level variables.

It should be further noted that the social background of immigrant students in traditional destination countries (e.g., Australia and Canada) compared to European nations such as Germany differ considerably, as these traditional destination countries select immigrants on the basis of skill and education (Entorf & Minoiu, 2004). What this means in the context of this study is that ethnic school segregation is only a minor factor among other more important variables (e.g., origin country, family background) (Dronkers & Levels, 2007). Overall, despite the recognition that there is an achievement difference between immigrant and native students on measures such as PISA, there is less agreement as to what factors account for it (Kao & Thompson, 2003). What is missed with pan-ethnic labels such as Asian or Hispanic is the diversity of social class differences within these groupings (Kao & Thompson, 2003). Ethnicity is not available within the PISA data set.

ESCS. In this study and for all nations selected, ESCS was a consistently positive and significant predictor at the student level across all domains in PISA 2006. Higher reported levels of ESCS were related to higher achievement. Germany recorded the smallest coefficient values for student-level ESCS, and the United States recorded the largest, across all literacy domains. Further details can be referenced in Tables 32–48.

Parental education and family income are possibly the best indicators of future educational attainment among youth (Kao & Thompson, 2003). Additionally, these differences are substantial across race, ethnic, and immigrant groups and account for a sizable proportion of

the variation in educational outcomes among these same youth (Kao & Thompson, 2003). Despite evidence that the link between SES and child well-being is a function of geography, culture, and immigration, interest in SES as a global construct persists (Bradley & Corwyn, 2002). PISA measures SES as a composite index of economic, social, and cultural status designed to capture student family and home background as well as occupational status (OECD, 2005a). PISA is in line with the literature reporting that a combination of income and occupational status data provides better estimations of SES than either of these alone (Bradley & Corwyn, 2002; White, 1982).

Although it is not easy to determine the processes through which SES influences child well-being, partly because low SES occurs concomitantly with other conditions that potentially affect children (e.g., immigrant status, single-parent family) (Bradley & Corwyn, 2002), these results are consistent with research on SES and school achievement (White, 1982). Sirin (2005) observed that the relationship between higher SES and increased academic achievement is contingent upon such factors as type of SES measured, student characteristics (e.g., immigrant status), and school characteristics (e.g., location). For example, immigrant status can also be correlated to lower SES as well as linked to lower academic outcomes (Marks, 2005), as was observed in this study. However, the literature is not definitive in this relationship (Blair & Qian, 1998; Schleicher, 2008).

Grodem (2008) studied Norwegian children to explore links between low SES as reported by parents and childhood experiences. She uncovered that although a clear correlation (r = .21) was reported between low SES reported by parents and deprivation experienced by children, children in immigrant families displayed more optimistic attitudes than non-immigrant children. It appears that concepts like low SES and deprivation are normative and interpreted differently

based upon previous experience and immigrant status.

Table 31 shows that adding the student-level variables of science self-efficacy, science self-concept, ESCS, and immigrant status as predictors of science, mathematics, or reading literacy reduced the within-school variance by approximately 20–30%. We can conclude that the combination of the student-level variables of science self-efficacy, science self-concept, ESCS, and immigrant status account for about 25% of the student-level variance in the outcome.

School-level variables. At the school level, both proportion of non-immigrant students and school ESCS were aggregated from the student-level data. As a result, their impact on the intercept at the school level is framed within the discussion previously concerning student-level variables.

For each nation and each literacy domain, the addition of mean school ESCS positively, consistently, and significantly increased the conditioned intercept by approximately half a standard deviation. That is, mean school ESCS had significant effects across all domains in addition to any effects at the student level. Portes and MacLeod (1996) argue that the positive effects of family SES on children's academic attainment should be stronger in schools where other children are also from higher SES backgrounds. This may be interpreted as schools with higher level ESCS provide more effective learning environments and therefore promote overall academic performance (Willms, 1992).

The only time the other school-level predictor (proportion of non-immigrant students) was found to be significant on the intercept was for New Zealand and mathematics. In this case, its addition reduced the intercept (i.e., −27.3) when the other independents are held constant. One interpretation of this finding is that schools in New Zealand with larger immigrant proportions lessen the impact of school mean ESCS. Although Byrk and Raudenbush (2002) have identified

the effects of attending schools with socially disadvantaged youth, there is also evidence for group membership creating a sense of collective dignity and resiliency (Blair & Qian, 1998; Zhou, 1997). Attending a school composed of individuals with similar learning needs as you can result in a greater possibility of these needs being addressed. For example, Rangvid (2007) discovered that even though more immigrant children attended lower SES schools in Denmark, educational resources designed to better meet their learning needs were more effectively delivered within those schools resulting in increased achievement.

Additionally and generally, the impact of the two school-level predictors—when significant on the student-level variables—increased the conditioned slopes, making the impact of these predictors greater. However, patterns across country and domain were inconsistent. In the case of mean school ESCS, significance meant that as a school increased its mean ESCS level, the influence on science self-concept, science self-efficacy, or ESCS was heightened. The interpretation of mean school ESCS predicting the effect of student ESCS on achievement is clear as students from a high SES background will benefit academically from an environment that is also high socio-economically (i.e., increasing inequality) (Sirin, 2005).

The modeled influences of school mean ESCS steepening the slope for science self-concept and science self-efficacy is more difficult to interpret. The relative ubiquity of the significant positive influence of mean school ESCS on science self-concept possibly has to do with the affective element of the construct. The school systems in the countries selected are part of an education paradigm that focuses energy and research on self-beliefs and student motivation (Pajares & Schunk, 2002). Science self-efficacy was only influenced positively in one instance for mathematics in the United States. An added level of complexity to this interpretive problem is that the ideas of science self-concept and science self-efficacy are conceptualized as domain

specific, yet were significant predictors across all three literacy domains in this analysis (see previous discussion on student-level science self-beliefs).

For school proportion of immigrant students (level 2), the slope for student-level ESCS was flattened, but only for New Zealand and Spain. Again, this is reasonable as the larger proportion of immigrants in a school may mediate the negative impact of immigrant status. This supports evidence of a positive neighbourhood association with achievement after the student level is controlled (Arum, 2000; Bradley & Corwyn, 2002). Larger numbers of immigrants would potentially create an environment that was more conducive (socially or academically) to immigrant student achievement. Immigrant children tend to do better than their American-born peers of similar SES background who attend public school in the same neighbourhood (Arum, 2000).

Finally, information on the proportional reduction in error compared to the null models for the addition of significant school-level variables was also calculated. These values can be interpreted as an effect size (i.e., proportion of variance accounted for) and are found at the bottom of Tables 32–48. The proportion of error variance reduction by the addition of significant school-level predictors on the intercept ranged from a high of 64% in Germany to a low of 8% in Canada. This represents a sizable range and is understandable given that the original amount of variance available for modeling also varied considerably with Germany's close to 60% and Canada's close to 20%. Interpretation of these values is limited because the level 2 random effects might be correlated with each other (see Tables 28–33), and predictors entered into one equation potentially influence variance on the other (Byrk & Raudenbush, 2002). To accommodate for this potential difficulty, the suggestion to enter the same predictors into each level 2 equations by Byrk and Raudenbush (2002) was followed. The main point to be taken

away here is that both school-level variables explained science achievement.

Limitations

There are a number of limitations to this study that need to be kept firmly in mind when reading and interpreting the results. These are presented below according to the methodology employed, analysis performed, and nature of the data set.

An initial concern comes from the methodology employed here (secondary data analysis), and a potential mismatch between desired and available variables exists. For example, the aggregated ESCS (economic, social, and cultural status) variable for socio-economic status was selected by PISA, yet the literature would support the inclusion of other additional measures of this predictor (Mueller & Parcel, 1981; UNICEF, 2007), and some evidence to this fact within this study has also been offered.

An additional limitation of note with secondary data analysis is that data often dictate the research question (Bell-Ellison & Kromrey, 2007). The student-level variables were selected with an eye to the research literature in this area; however, the school-level variables were not and constitute aggregated student-level variables. If additional variables at the school level that might have better captured SES had been collected (e.g., presence of a hot-lunch program), these would have been selected instead. (Similarly, as these student-level variables were also indices according to PISA guidelines, some care must be taken when interpreting their results. These variables were ultimately decided on by the author, and limitations follow.)

Correlation, regression, and multilevel models (i.e., HLM) are exploratory rather than confirmatory tool, and the results here, although reported for significance, cannot suggest or confirm causality. Although this might seem routine, it is often forgotten. Statistical tools such as the ones used here only show that variables are related in a systematic way and do not prove or

disprove that the relationship is cause and effect. Rather, results are discussed within the context of previous research, and only further research is suggested.

Lastly, the originating country from which immigrant students arrive has a great deal of influence upon their subsequent approach to and success with academics. Kao and Thompson (2003) argue that large pan-ethnic labels fail to capture the large variability in immigrant groups, and both cultural groupings as well as the structural positions these students find themselves in upon arrival greatly impact academic achievement. To collect data on these background variables and how they relate to academic achievement would give a clearer picture of immigrant students' experiences and render the findings from studies such as PISA more useful.

However, despite the concerns and limitations, the results here do have utility for educators and researchers interested in exploring what might work best across nations and in classrooms. As an exploratory investigation into what classroom environments might be conducive to promoting scientific literacy and how nations might best aid immigrant students in being academically successful, some ideas are offered here.

Recommendations

There have been occasional comments made throughout the discussion section of this study that suggest future research. In addition to these, there are some general recommendations that arise from the work detailed above.

The first deals generally with comparative and international education. As Crossley and Watson (2003) argue, the more educational researchers engage with comparative and international studies, the more insights and benefits, both intellectual and professional, will accrue. However, this must be tempered with the recognition that simplistic assumptions about the transferability of policy and practice have not been uncovered (Creemers, 2006). There is

already much evidence in the existing literature to suggest that improvements to the quality of education cannot be imposed and that "universally applicable" models of educational reform are highly problematic (Crossley &Watson, 2003).

Another area that emerged from this study that requires further attention is the relationship between science self-efficacy, science self-concept, and science literacy. One of the striking results from this study was the finding of negative relationship of science self-concept to achievement in the East Asian countries. Leung (2002) comments that self-confidence and self-image in East Asian societies are low because of two things: first, those students are constantly taught to rate themselves low; and second, high expectations on examinations result in many being labeled as failures. Nonetheless, the negative science self-concepts of the East Asian students did not seem to affect individual achievement.

An interesting line of research begun by both Ross (2008) and Hsu (2007) would be to explore the self-concept and self-efficacy levels of immigrant students who have come from countries with relatively low self-concept and self-efficacy levels to countries with high self-concept and self-efficacy levels in order to see what changes might result due to instructional practices.

Implications for Educators

A positive relationship between science self-concept as well as science self-efficacy and achievement might be an important characteristic to nurture in students. However, there is some suggestion that there may be cultural differences that influence the concept of self as it relates to achievement. In order to foster self-beliefs in the science classroom, Britner and Pajares (2001) suggest authentic and inquiry-oriented investigations that offer mastery experiences, group interactions that are collaborative and not competitive, as well as appropriate and realistic

feedback opportunities. Wilkins (2004) believes in the importance of educators to help students maintain positive views about themselves as scientifically competent. Despite evidence attesting to the powerful nature of these constructs, specific and workable strategies for enhancing these beliefs that translate into meaningful outcomes is scarce (Bong & Shaalvik, 2003).

The other two recommendations relate to the concepts of SES and teacher attitudes toward students in the classroom. Background student variables such as cultural and social capital could be reasonable places to intervene to improve student achievement. This study has uncovered a sizable amount of variance that is accounted for by cultural and social capital. Both of these forms of capital could be positively influenced through enriching materials and experiences that engage cognitive arousal and development. Learning materials and experiences related to scientific thinking that are outside many students' day-to-day routines afford opportunities for social exchange and this social arousal mechanisms in a productive way (Bradley & Corwyn, 2002). Offering simple education experiences to parents in their homes encouraging them to have the right factors in place (i.e., access to expository text) will help their children to succeed academically (Milne & Plourde, 2006). Hattie (2009) further suggests that as parents can advantage their children academically by helping them know how to "speak the language of schooling" (p. 33). Thus, schools can play a key role in helping parents to learn the language of school so that they can assistant their children in learning and love of learning.

Finally, teacher attitudes and expectations may also be part of the complex array of mediators that link immigrant status as well as low SES students to school failure. Research has uncovered that teachers perceive low SES students and immigrant students less positively (Bradley & Corwyn, 2002; Rangvid, 2007). As a result, these students will experience less positive attention and feedback for behaviour crucial to their development. Unfortunately, if

children both prior to school entry and during early schooling have less experience with cognitively stimulating materials and experiences at home, they will fulfill teacher stereotypes (Rangvid, 2007) and be caught in a negative loop.

The largest caveat here to any recommendation is the difficulty of inferring casual relationships for policy purposes from data that are correlations, as there are problems of comparability between education systems that have differing aims and curriculum (Goldstein & Thomas, 2008). The best suggestion here is for localized and contextualized interpretations of these results.

Conclusion

The aim of this study was to uncover the relationship between scientific literacy and science self-efficacy and science self-concept. Additionally, the predictive effects for science self-beliefs, immigrant status, and SES on scientific literacy were further explored for a select group of nations involved in PISA identified as experiencing high immigration.

Science self-concept and science self-efficacy were found to correlate positively with higher scientific literacy at the student level. However, at the country level, science self-efficacy was positively but non-significantly correlated with scientific literacy, and science self-concept was negatively and significantly correlated. Additionally at the country level, the countries that ranked lowest on science self-concept (primarily East Asian countries) performed highest on scientific literacy. A pattern between science self-efficacy and science literacy was not observed. This finding is consistent with literature that recognizes the social comparison aspect of self-concept (Marsh & Craven, 1997) and the highly skilled students and frequent student comparisons made in the East Asian education systems (Lueng, 2002).

The construct of SES is a complex measure. Although generally accepted to be comprised

of some combination of income, occupation, and education (Bradley & Corwyn, 2002), there is some dissention as to the balance of these components. It was uncovered here that cultural capital and social capital were the two most important explanatory constructs for scientific literacy. This was not unexpected based upon the relative wealth of the nations that were involved in PISA 2006. However, what is potentially promising from this is that schools and education systems have an opportunity to improve measures such as social and cultural capital within their systems through more openness and transparency.

There was relative consistency across the models presented here for the nations of high immigration. Almost without exception, immigrant status, science self-beliefs, and SES were significant predictors at the student level. Similarly, school SES was the most consistent school-level predicator on the intercept value. These finding suggest that some of the instructional recommendations offered here for helping students improve science self-beliefs are potentially generalizable across nations and cultures.

Concern for the current lack of scientific literacy in the population of many nations as well as efforts to define it has been chronicled by DeBoor (2000). This study informs and builds on cross-cultural comparative theory by examining if differences in academic achievement are associated more with individual student or school membership. As the world continues to see larger numbers of peoples migrating to the nations of Europe, North America, and Oceania, an understanding of how best to aid students from differing cultures in the achievement of scientific literacy is important if we are to best meet the needs of all students in our society.

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Appendix A: Ethics Waiver

Dear Todd Milford:

Please be advised that your Application for a Waiver from Full Ethics Review
Entitled 'An Investigation of Science Achievement Using the OECD's PISA 2006 Data Set' has been approved and assigned Protocol Number 09-092.

Beginning January 2, 2008, as per federal regulations, ethics protocols will be approved for a one-year period. All Principal Investigators are required to submit a Request for Annual Renewal form prior to the Certificate Expiry Date to maintain ethics approval. You will be contacted via email with details of Renewal submission approximately six weeks prior to the expiry date on your Certificate of Approval.

You may begin your research and will receive a Certificate of Approval of Waiver via regular mail.

Good luck with your Study.

Emily Little | Human Research Ethics | University of Victoria | Administrative Services Building - 2nd Floor | Victoria, BC | Canada | Tel: 250-472-4545 | FAX: 250-721-8960 | http://www.research.uvic.ca | E-mail: ethics@uvic.ca

Appendix B: Histograms of Variables Used in the Correlation and Regression Analysis: Science Self-concept; Science Self-efficacy; Science - Focus on Application; Science - Hands on Activities; Science - Interactions; Science – Investigations; Wealth; Home Possessions; Cultural Possessions; Books in the Home (ST15Q01); ISCEDL; HEDRES; HISEI; ESCS, IMMIG All Countries

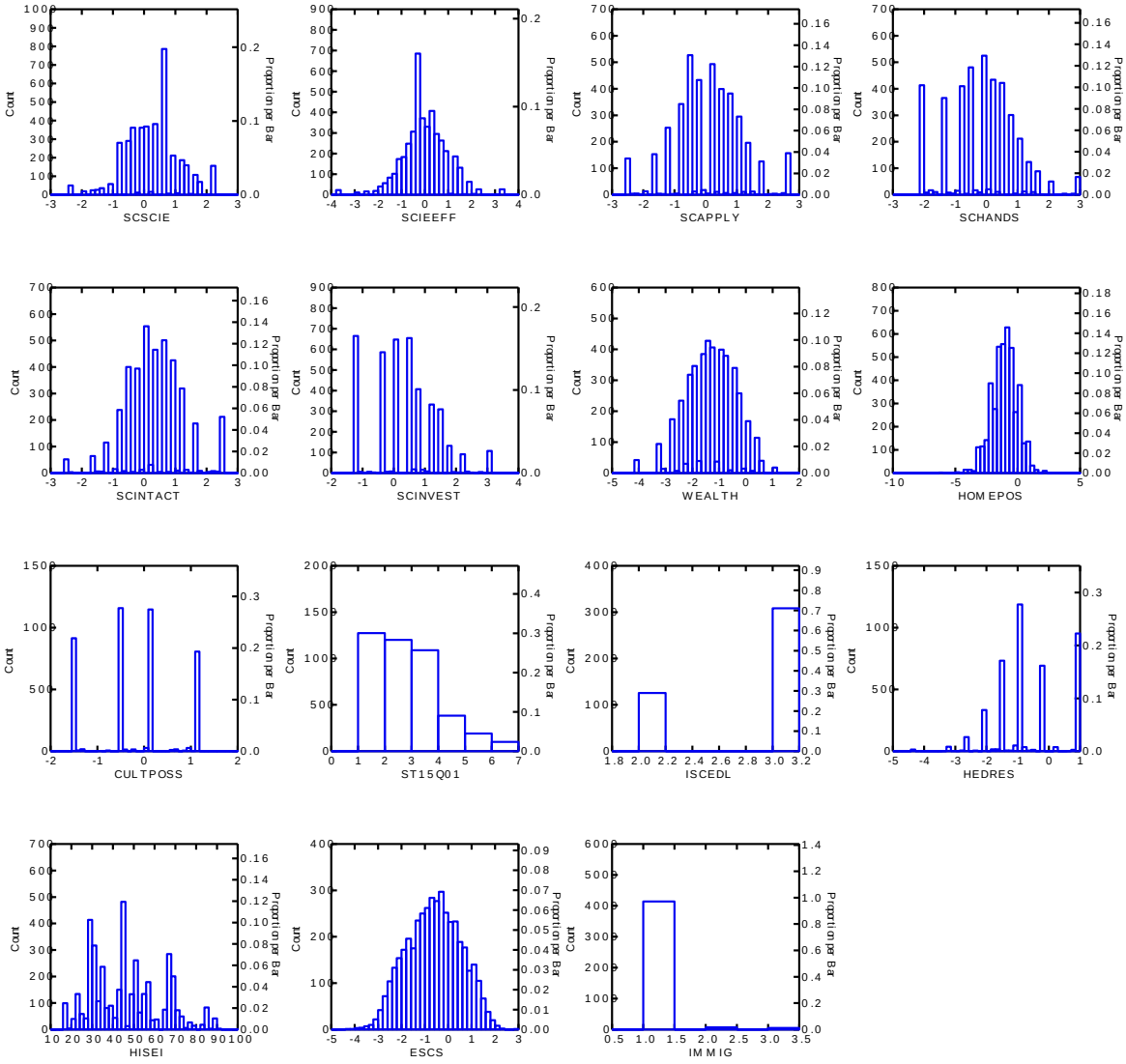
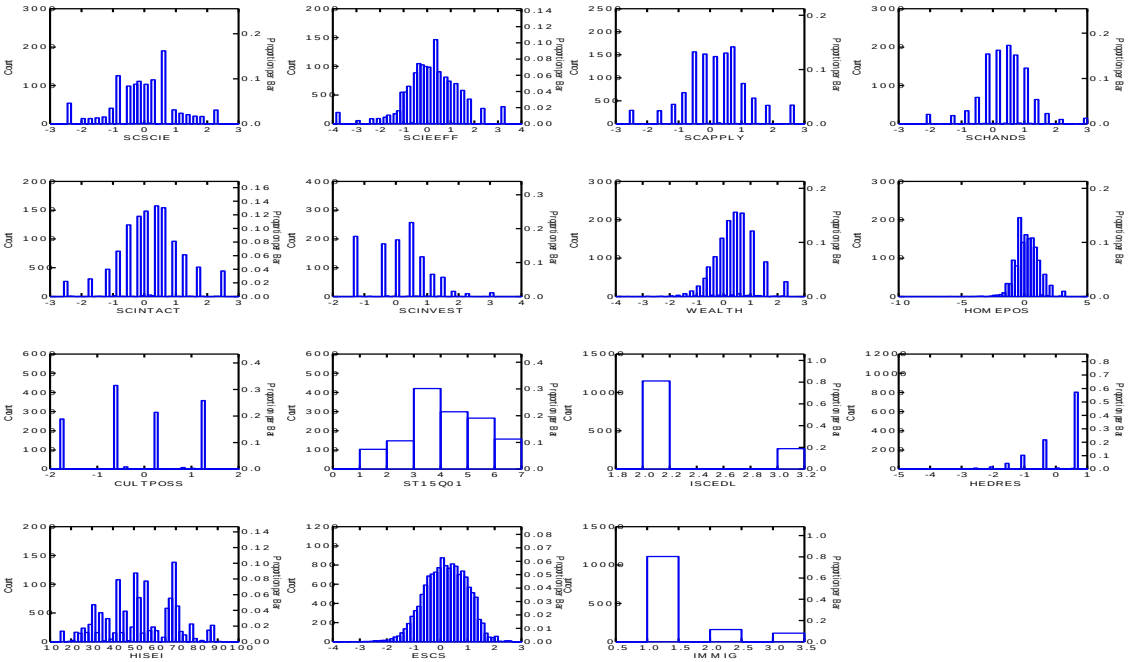


Figure B1. Argentina.



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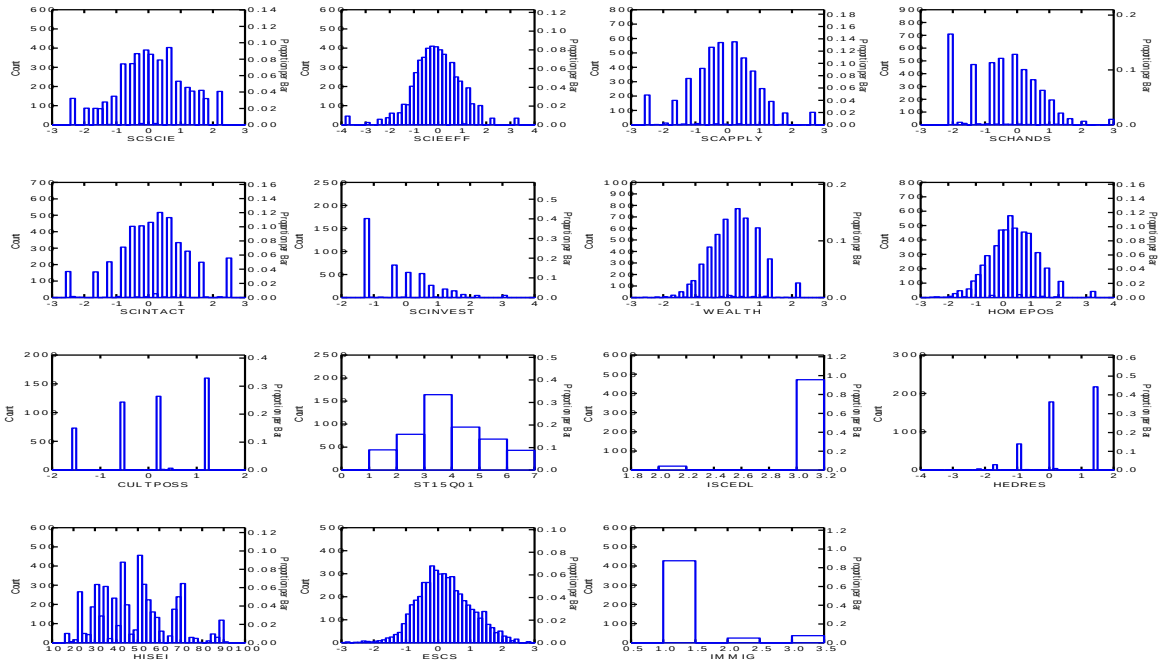

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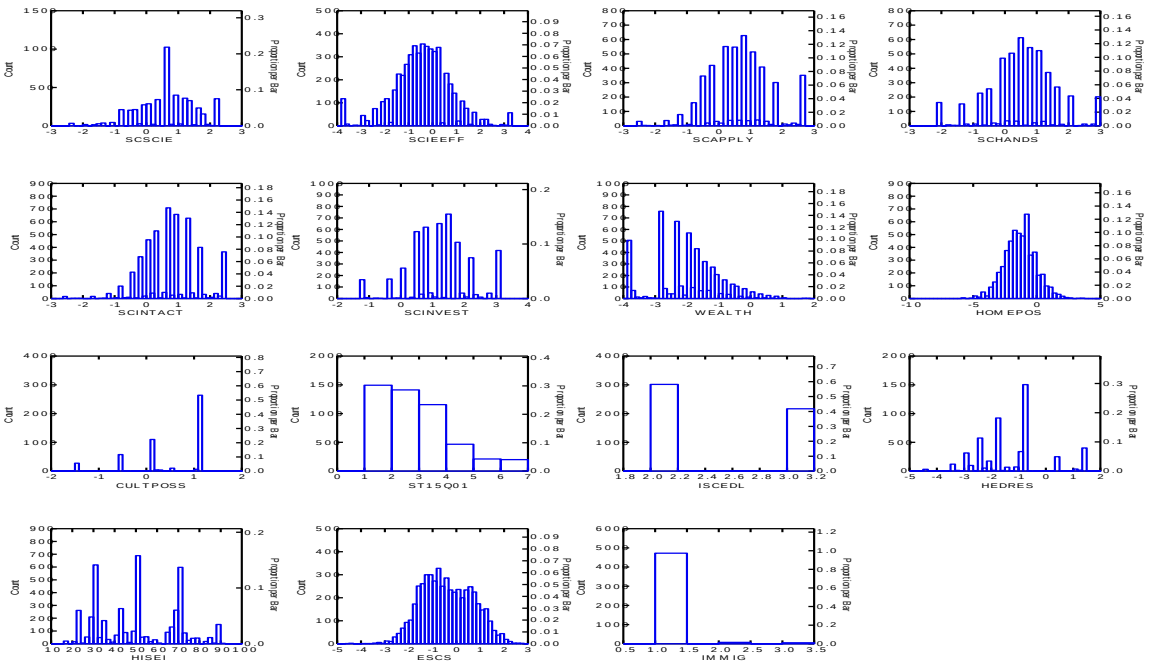

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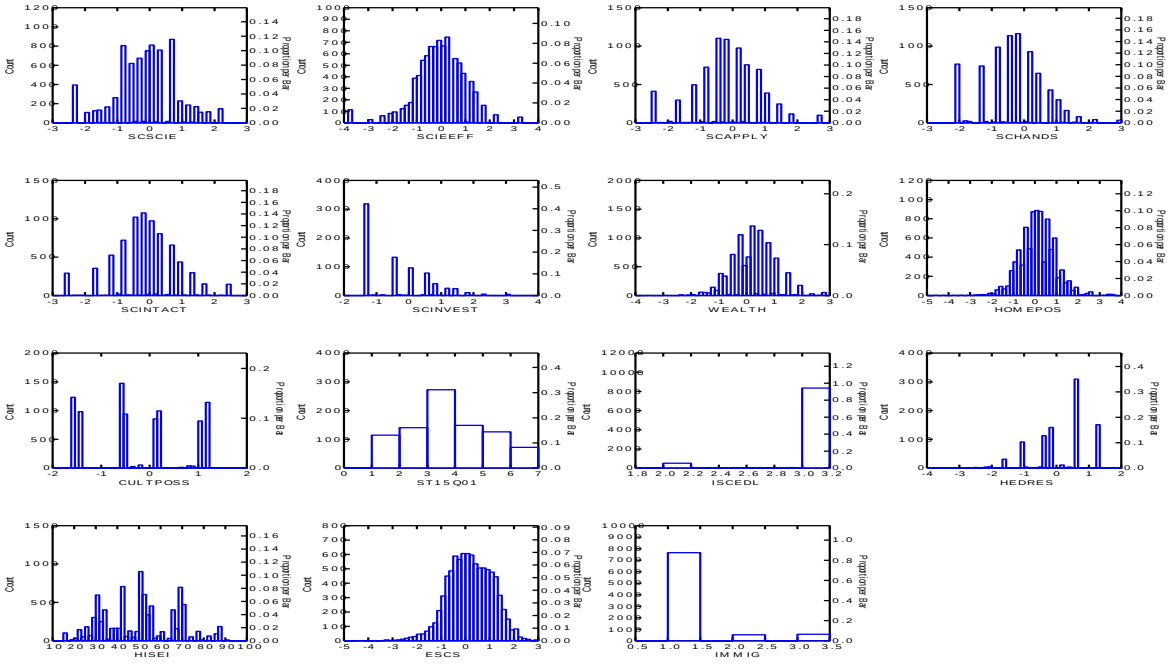

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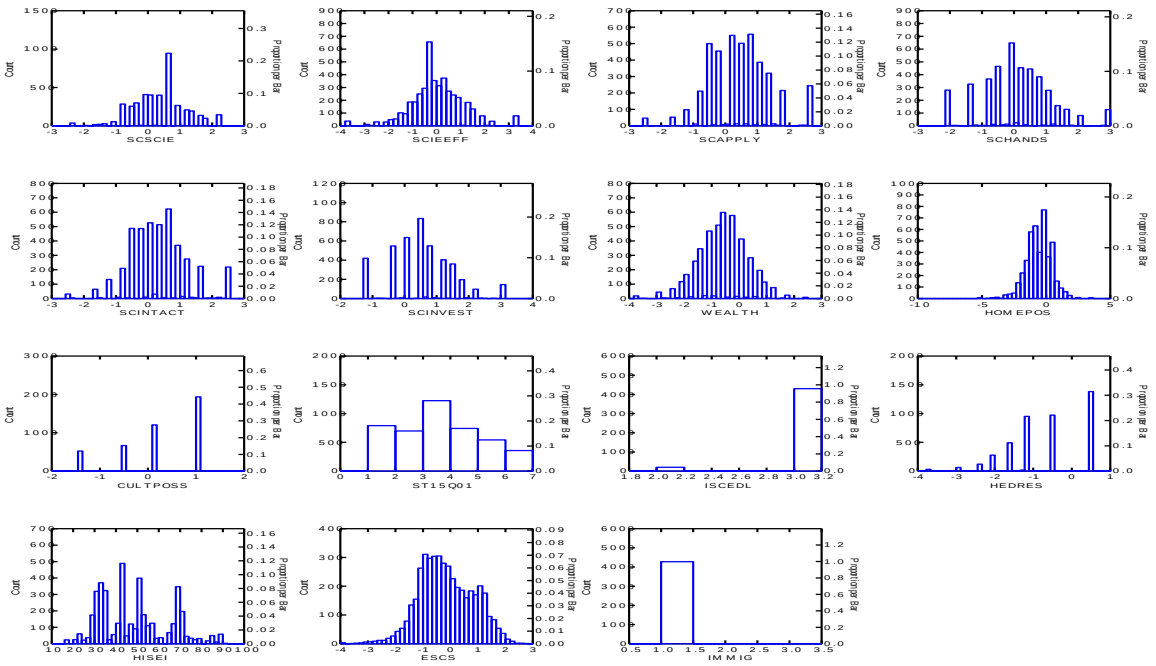

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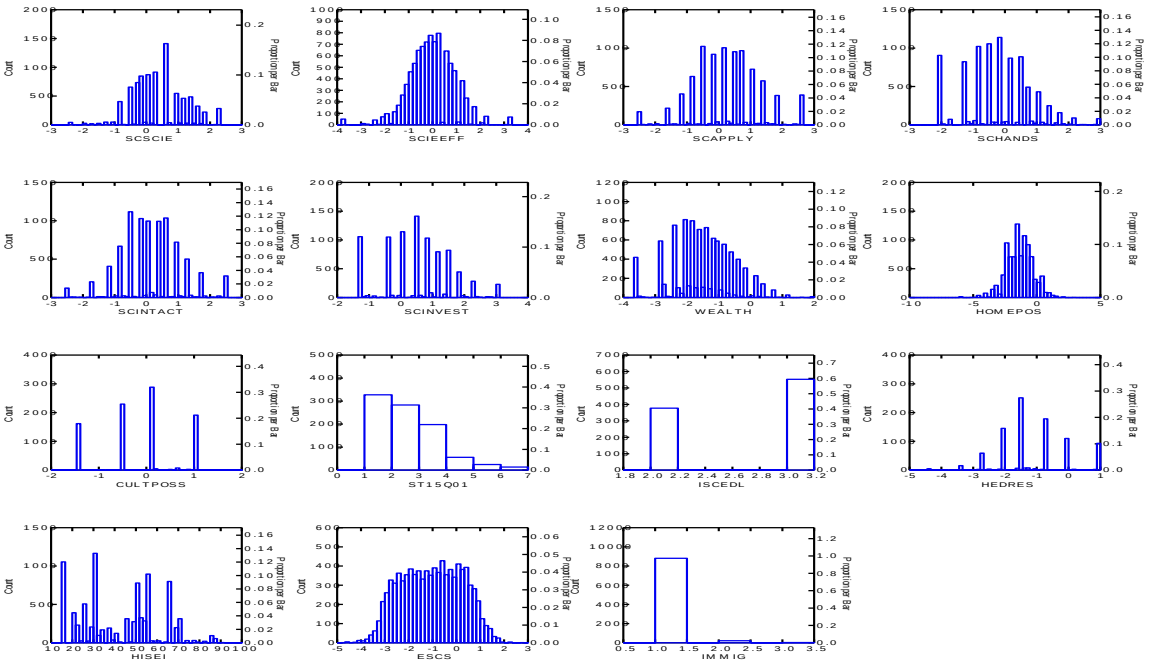

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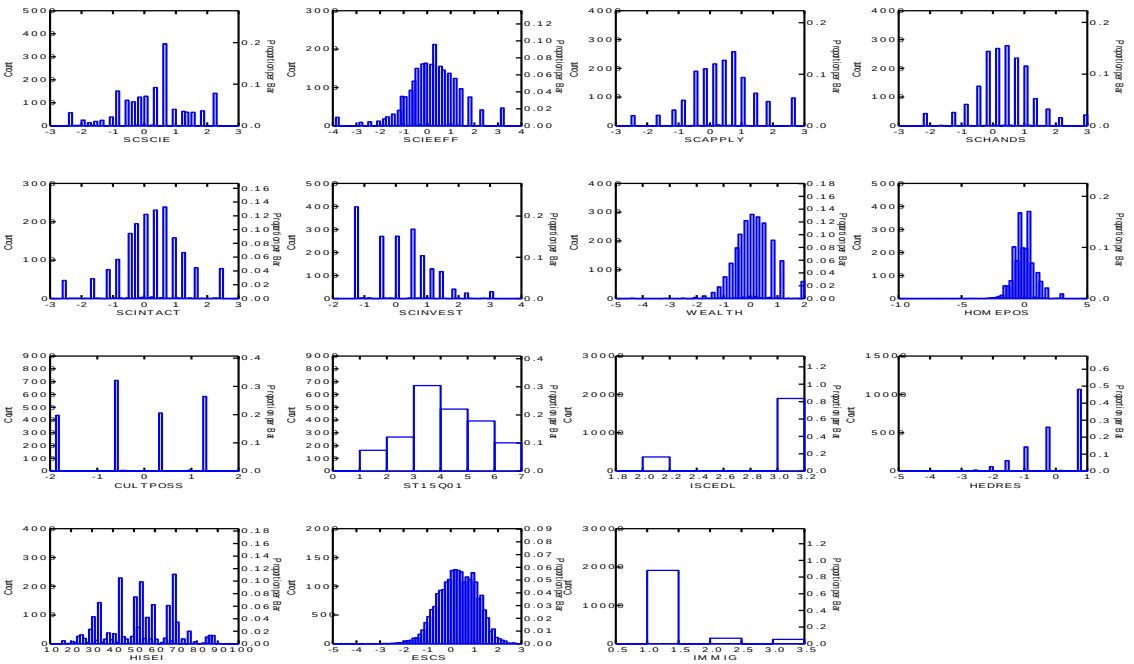

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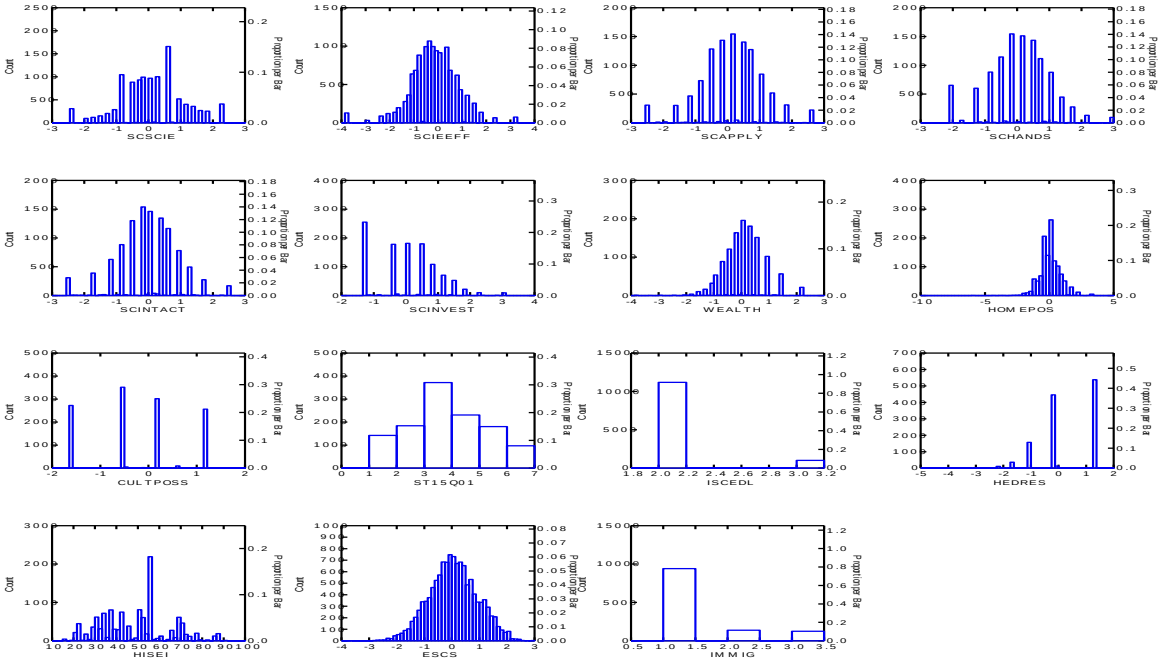

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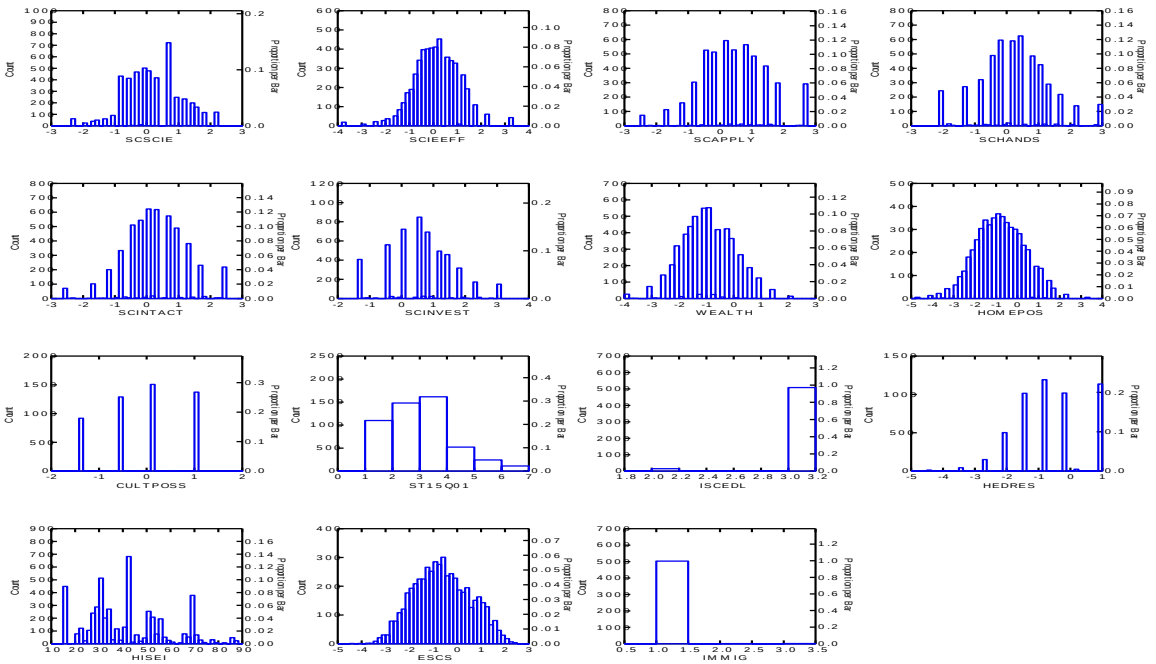

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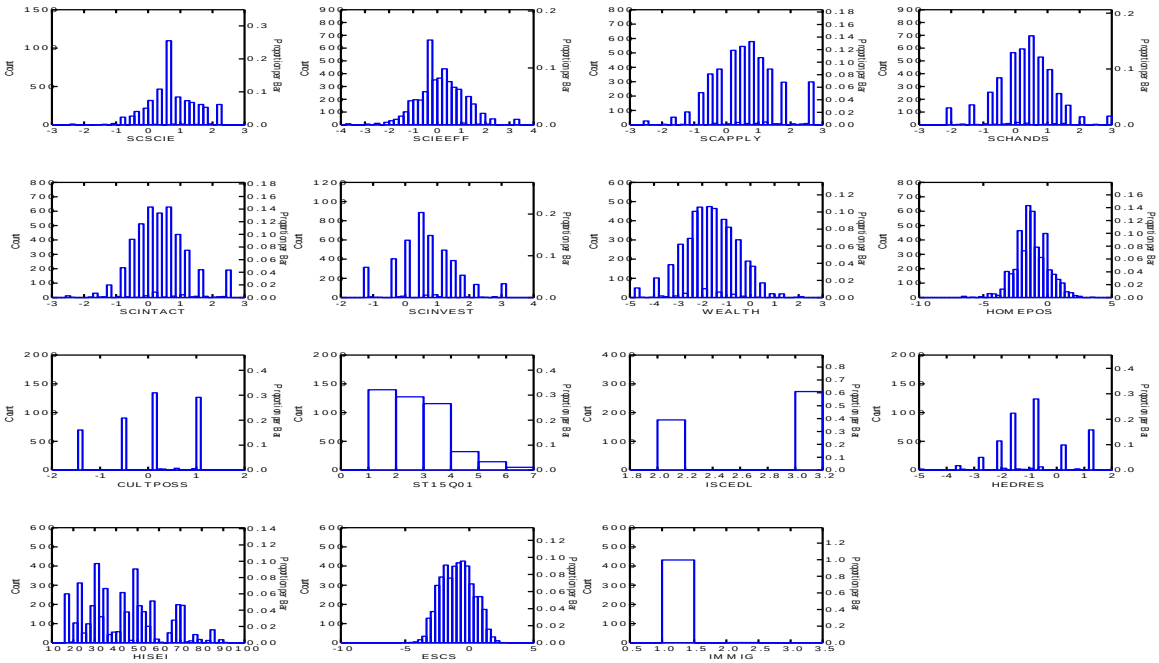

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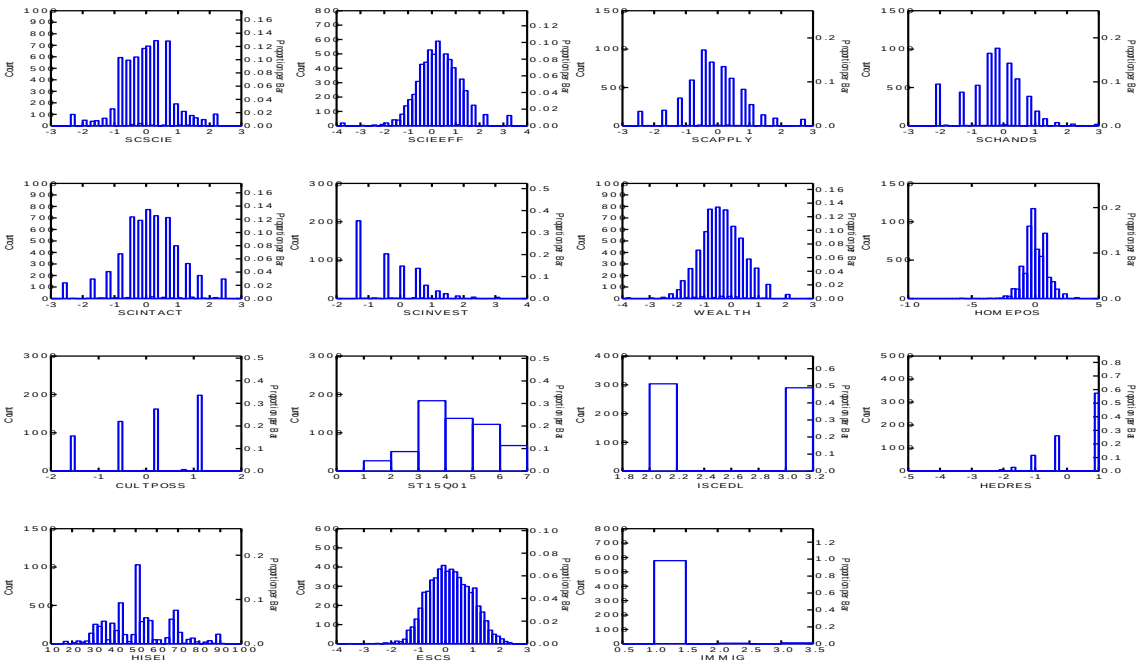

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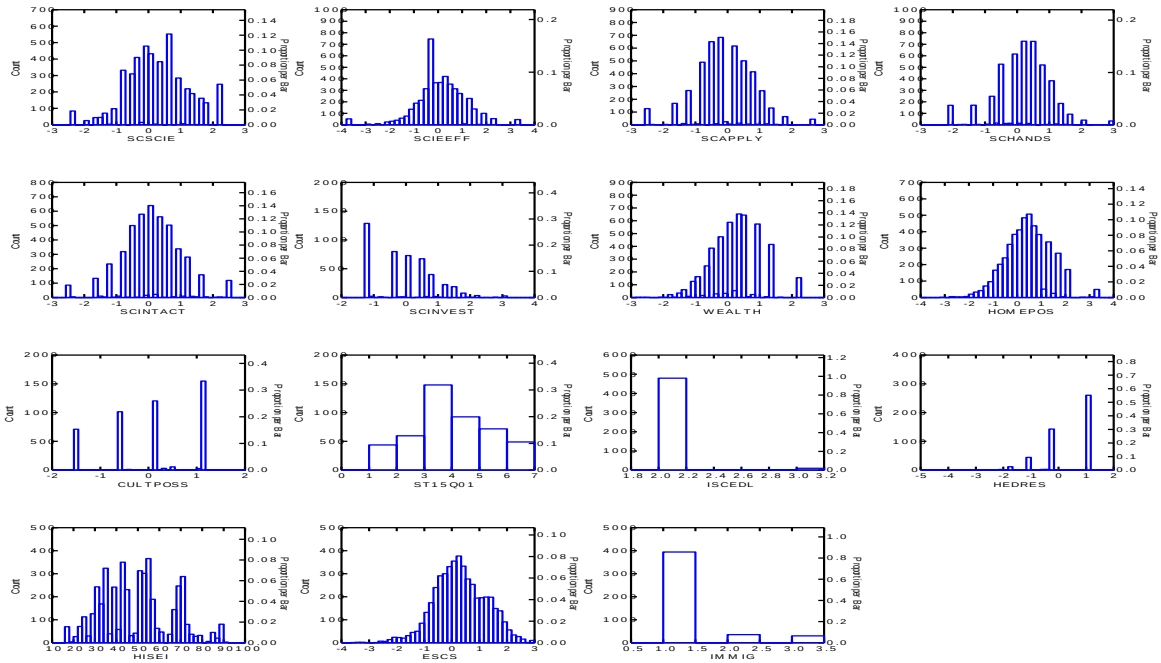

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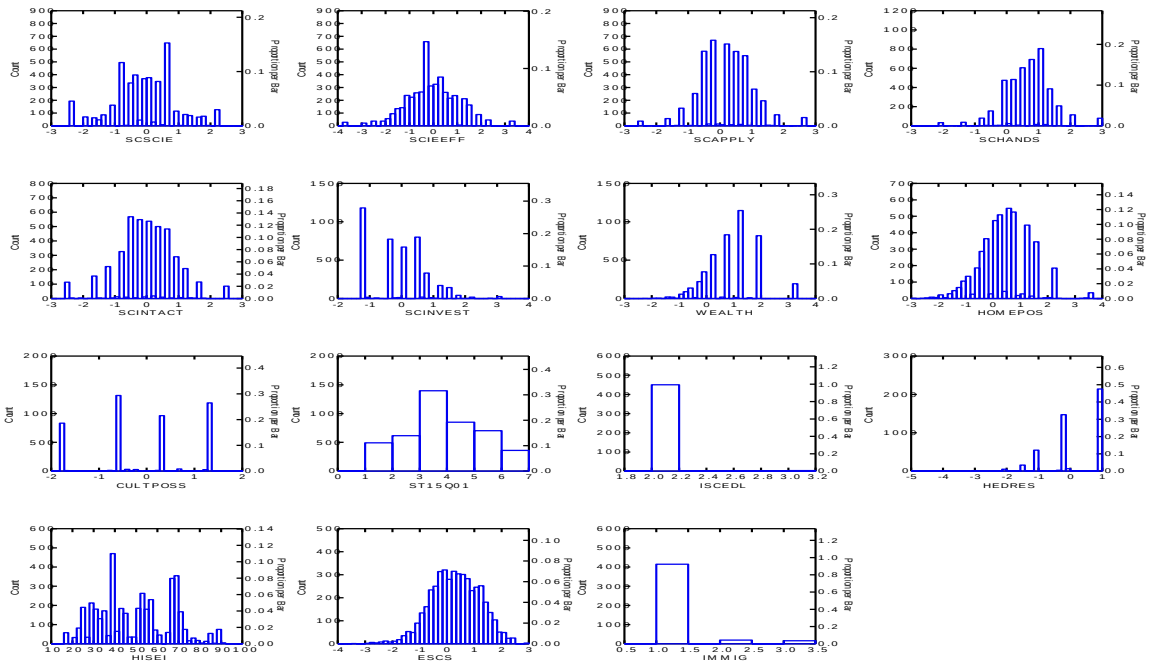

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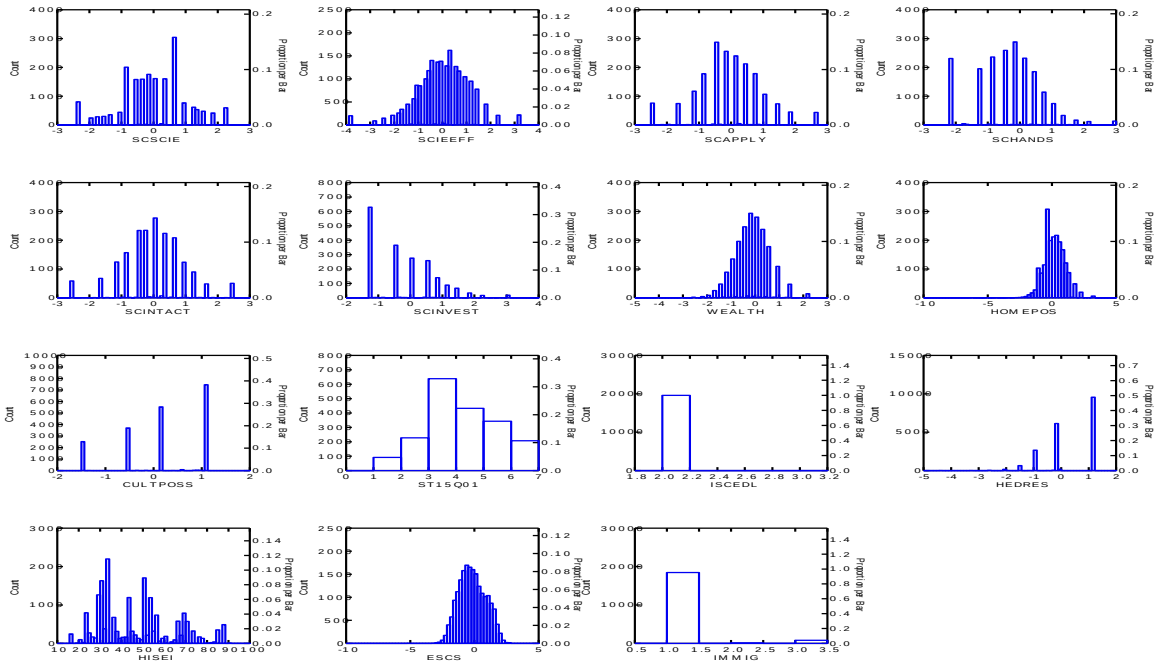

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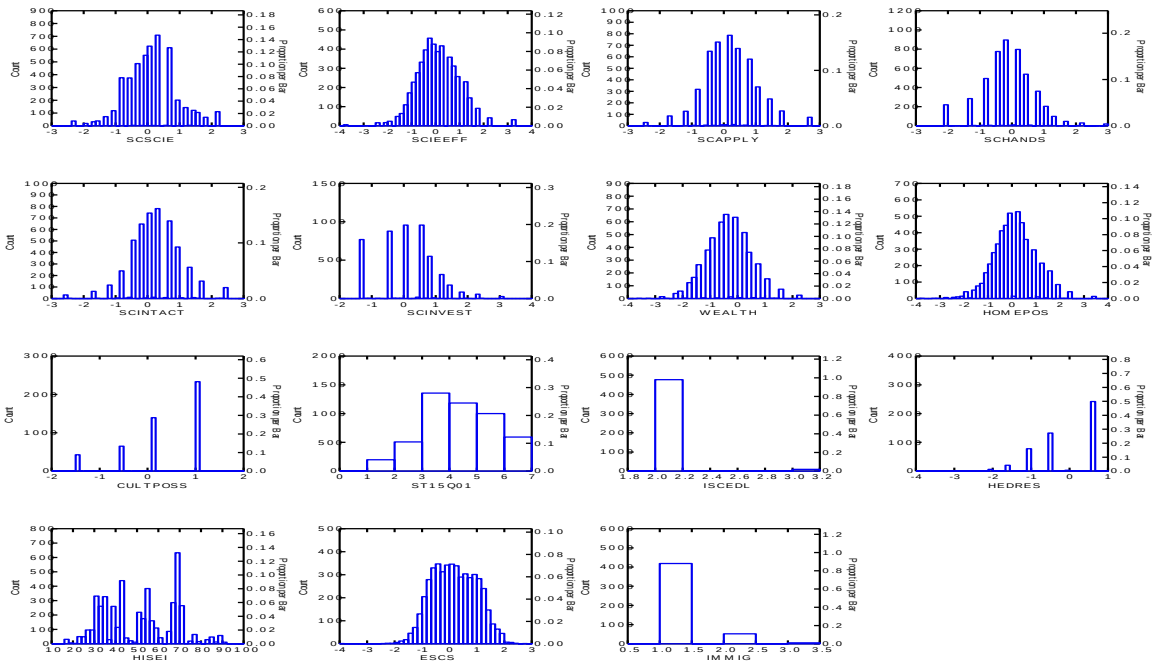

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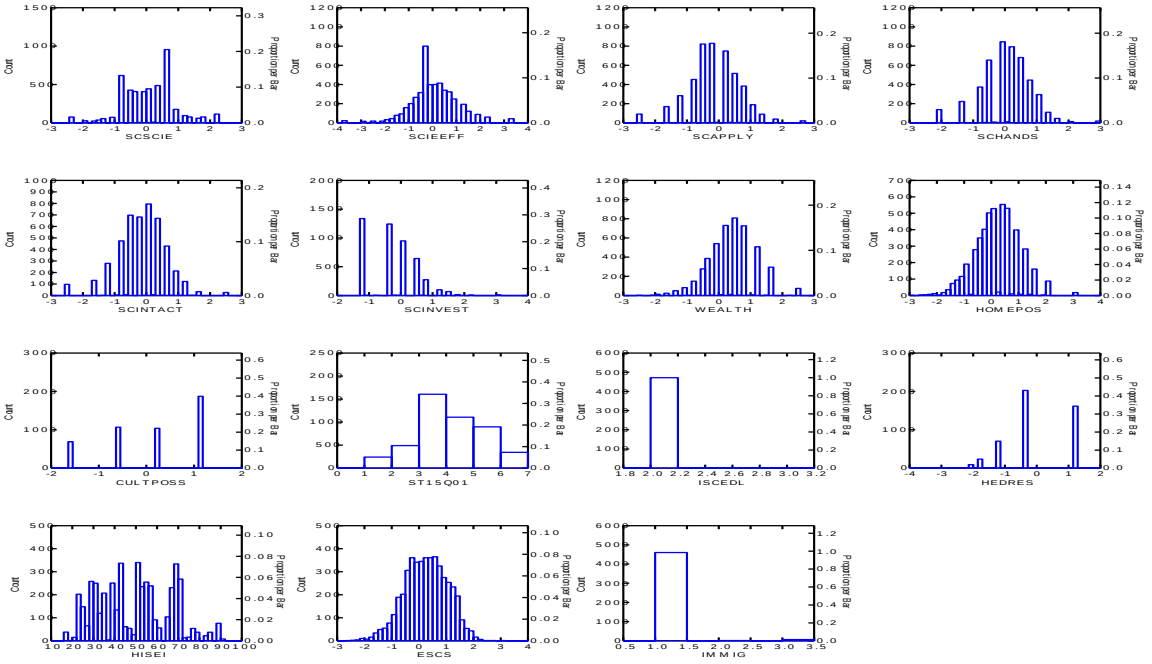

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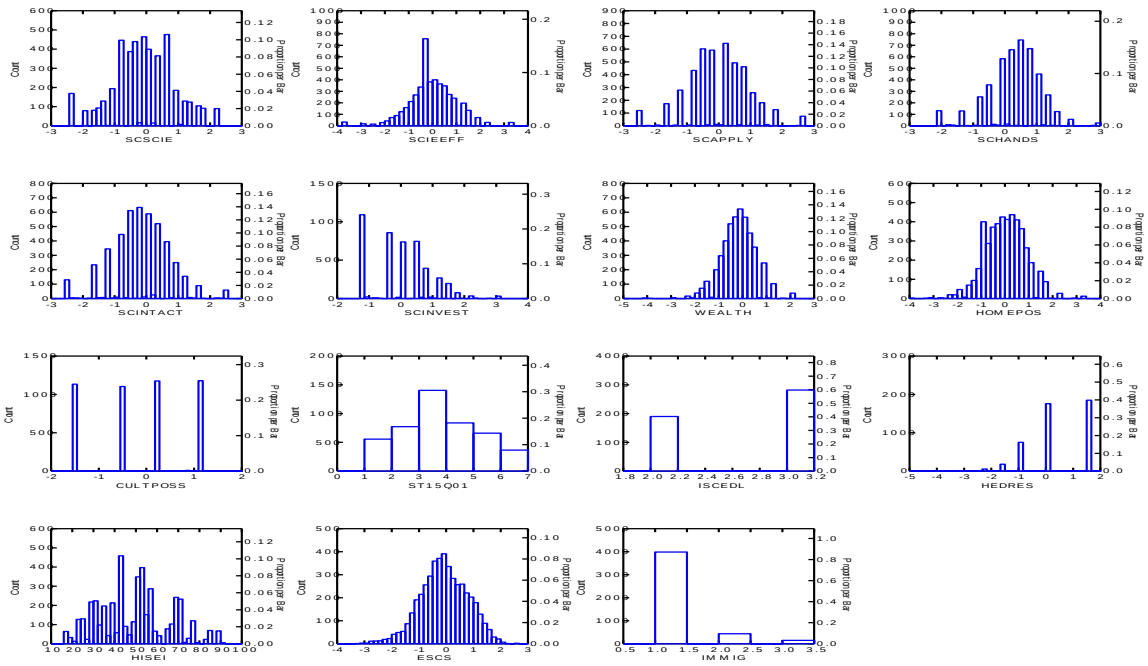

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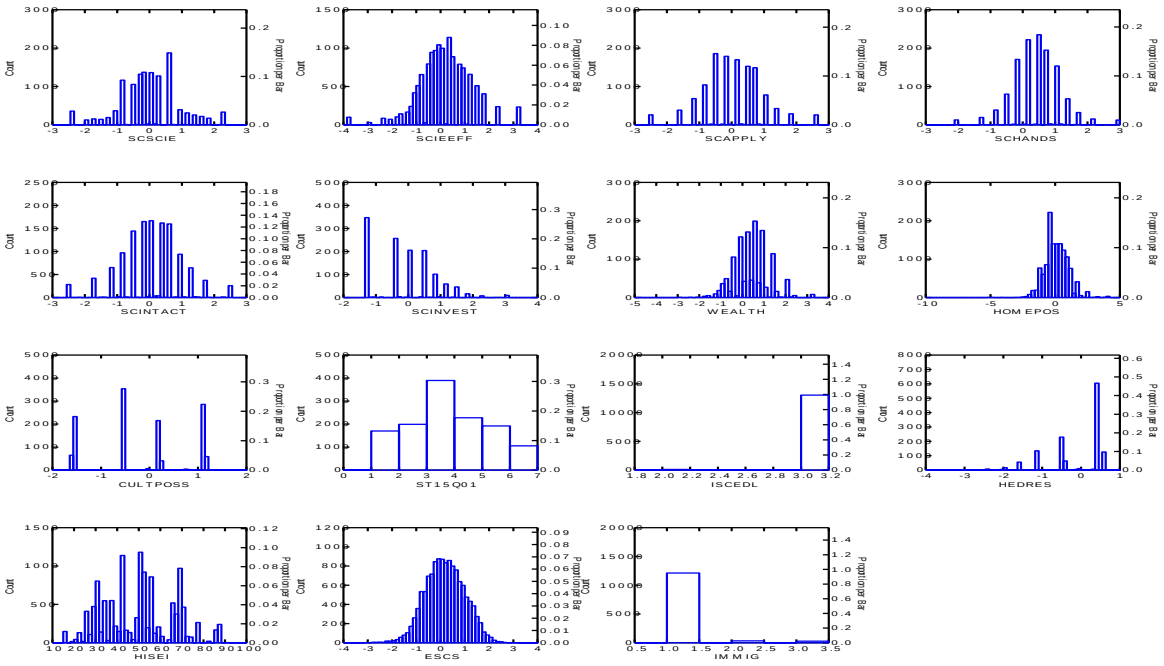


Figure B19. United Kingdom.

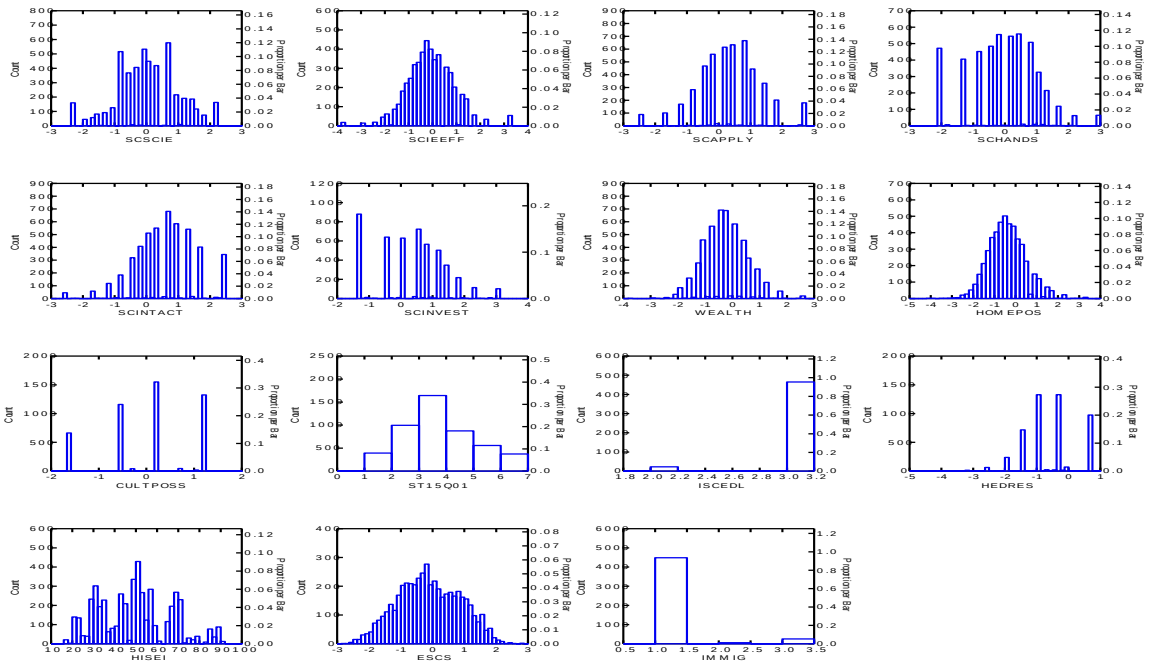


Figure B20. Greece.

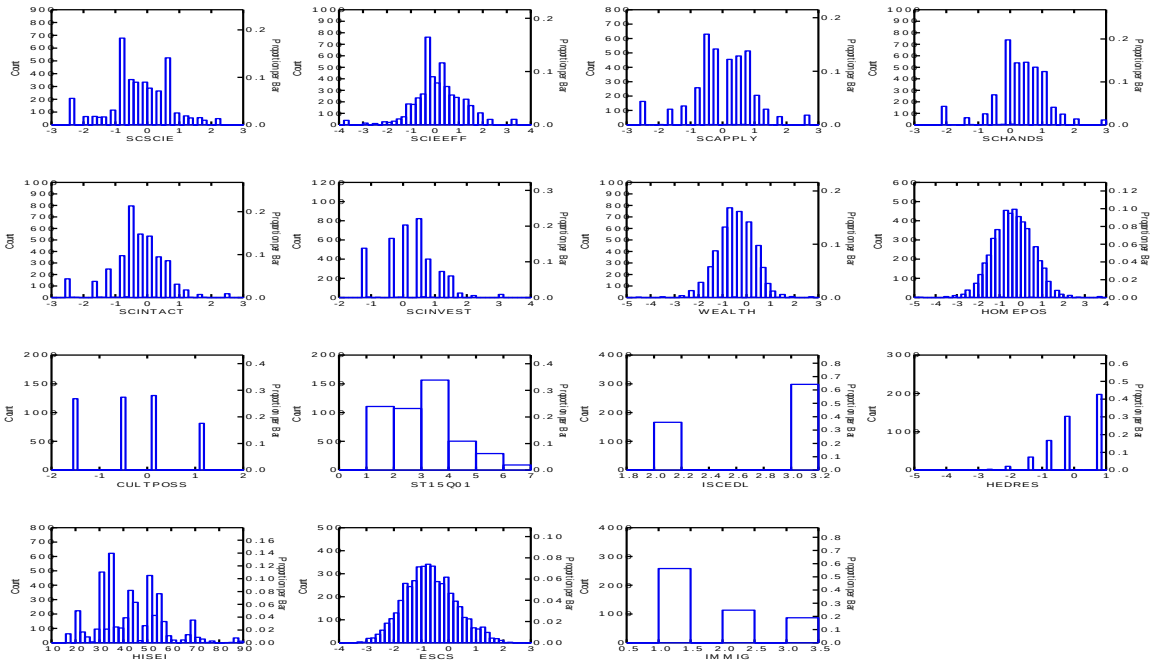
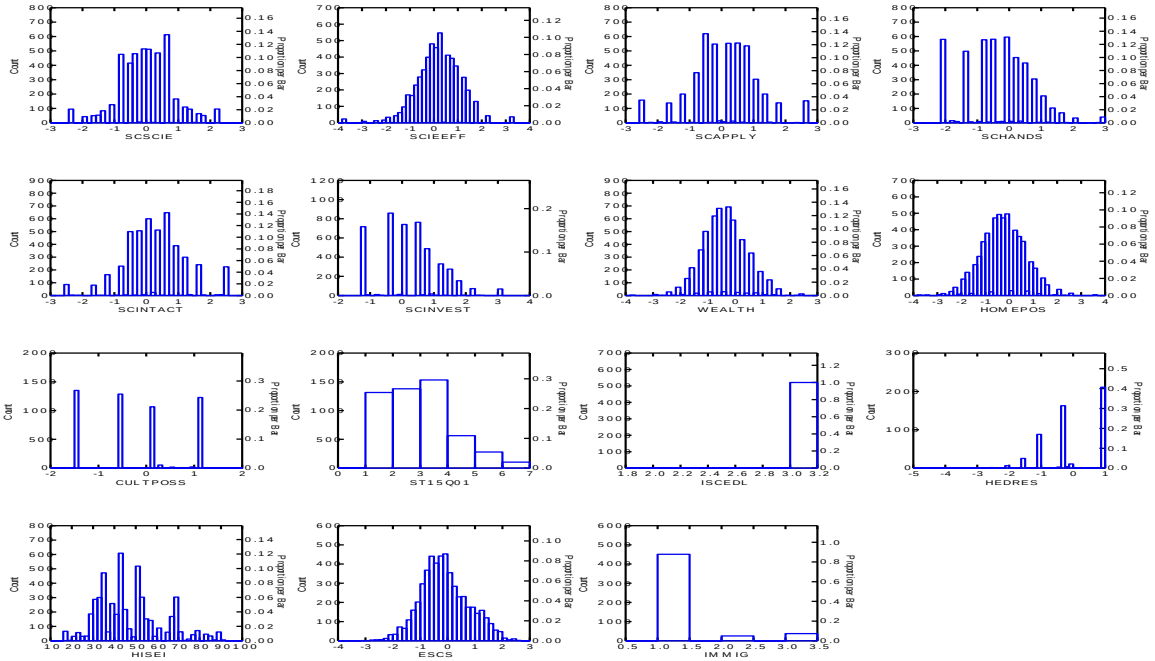


Figure B21. Hong Kong-China.



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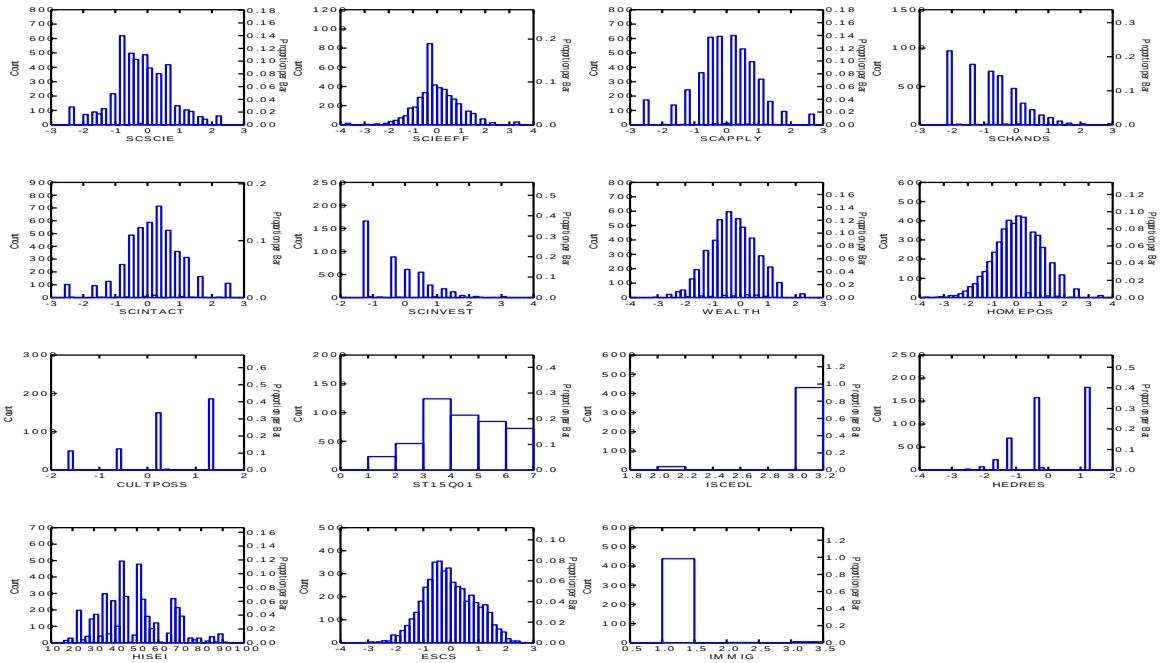

Figure B23. Hungary.

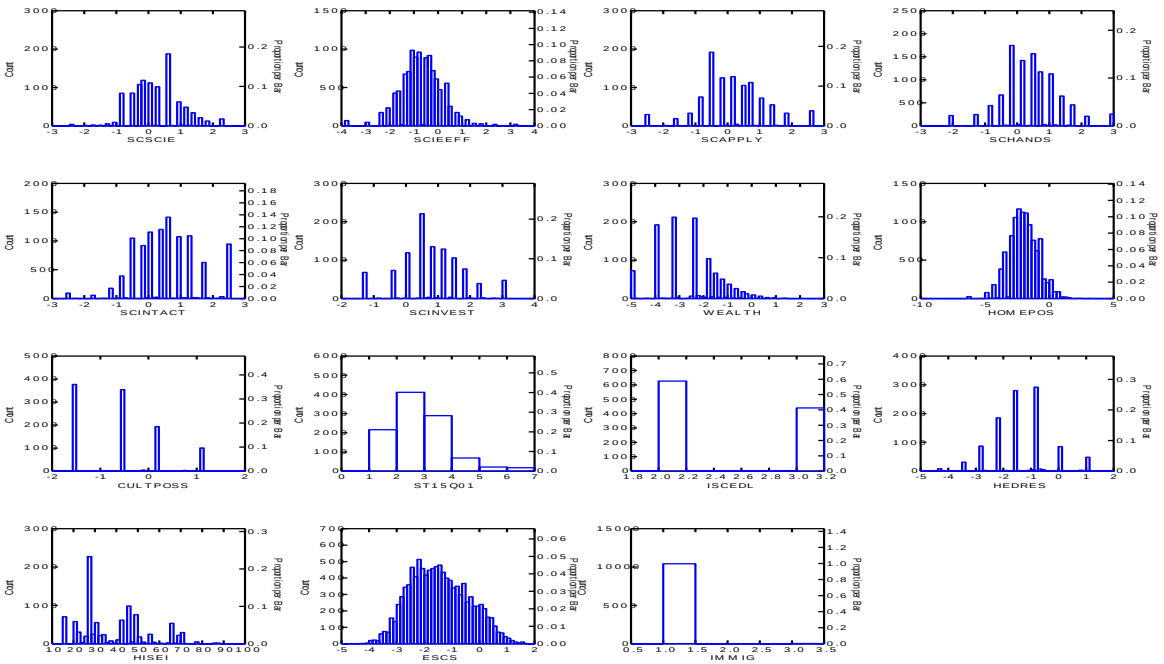

Figure B24. Indonesia.

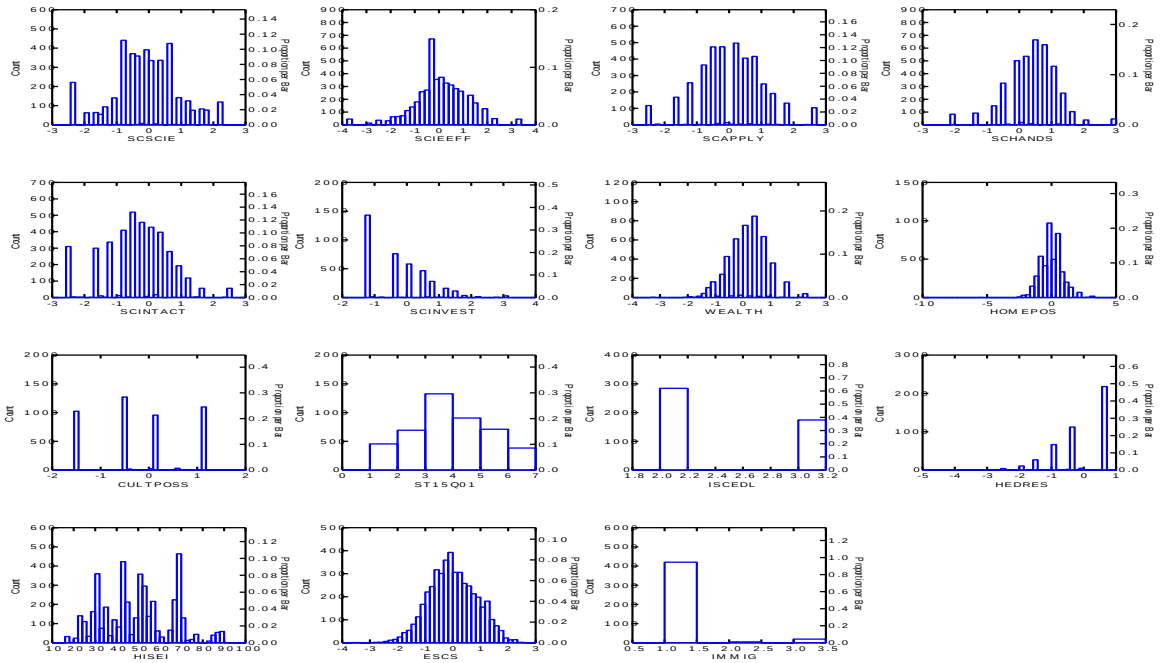

Figure B25. Ireland.

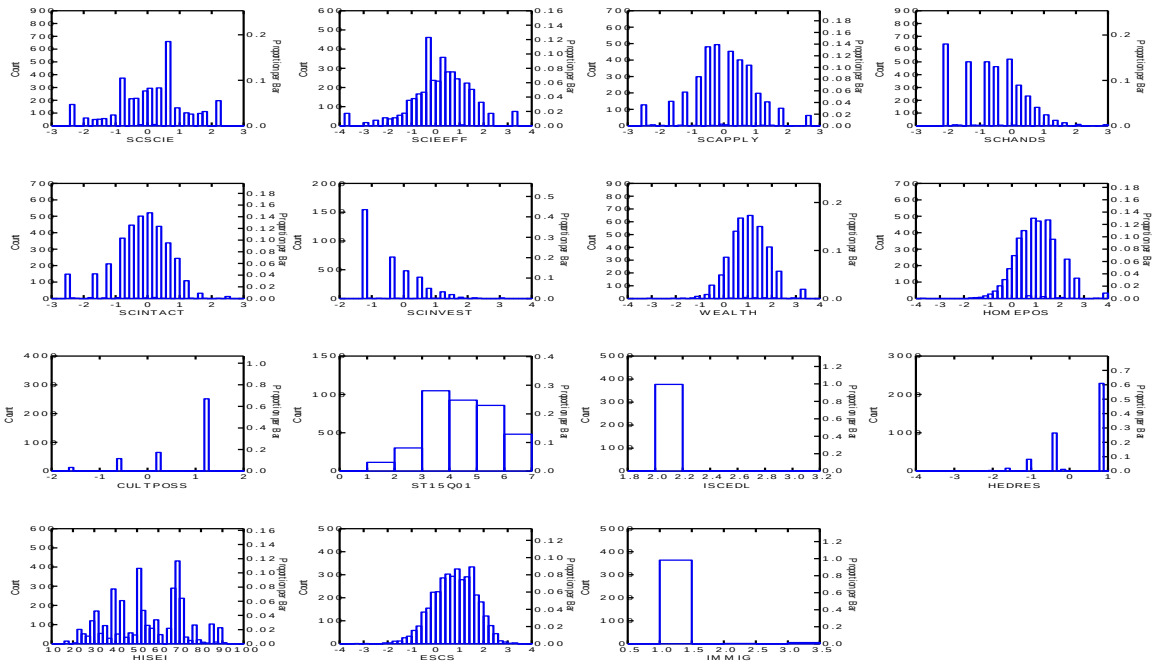

Figure B26. Iceland.

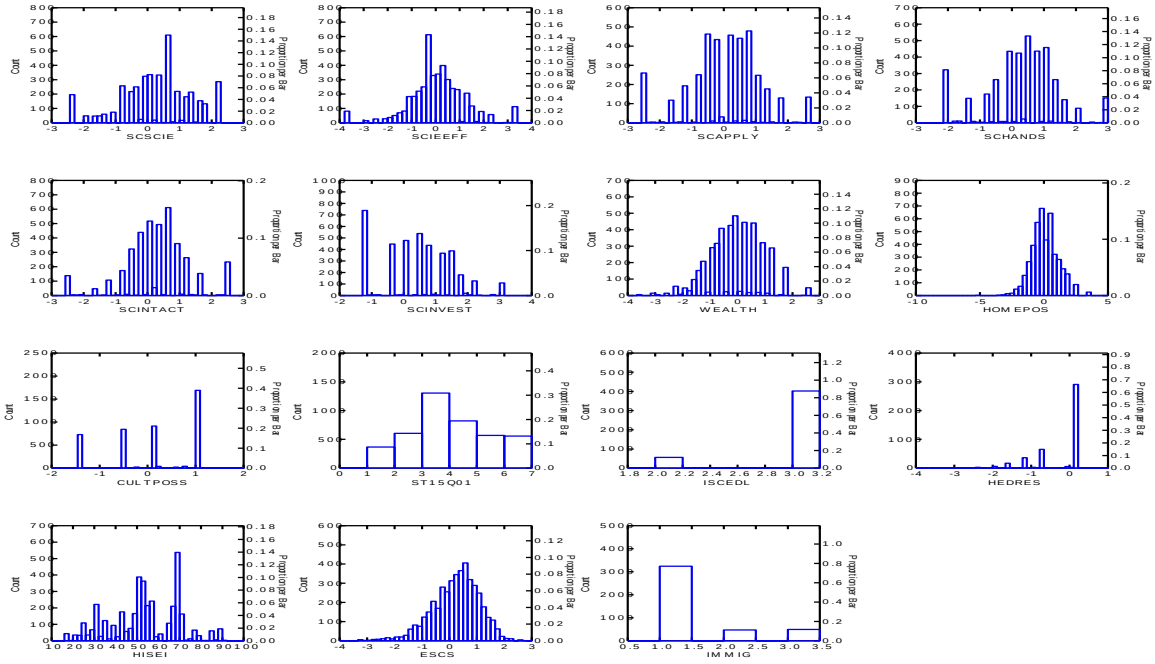

Figure B27. Israel.

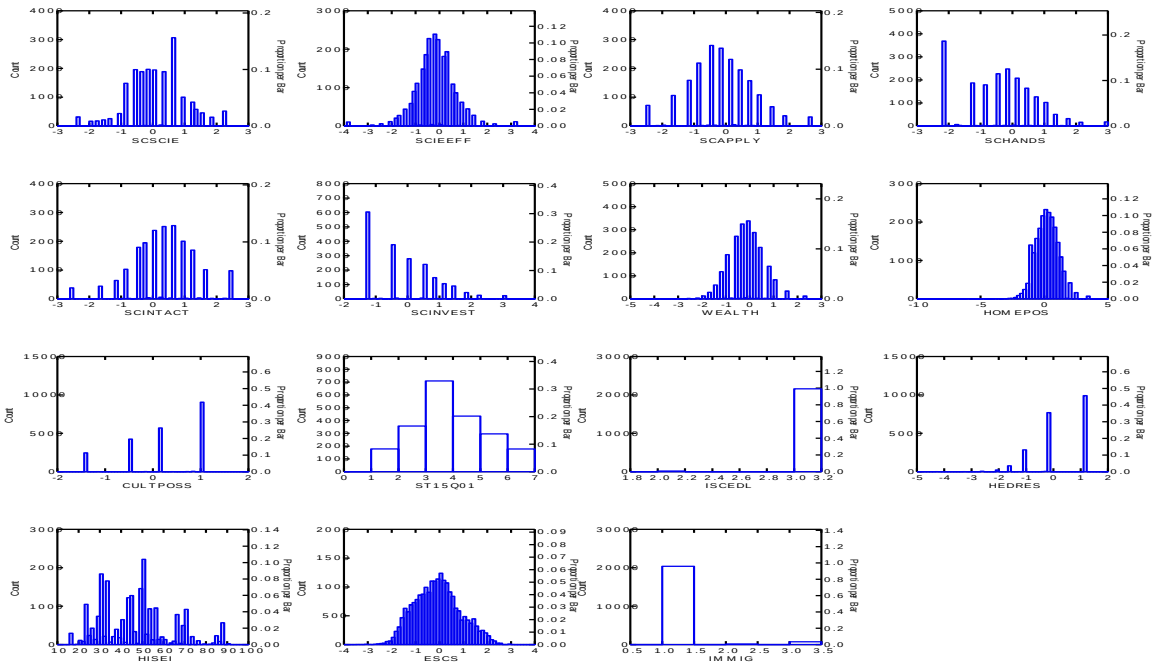

Figure B28. Italy.

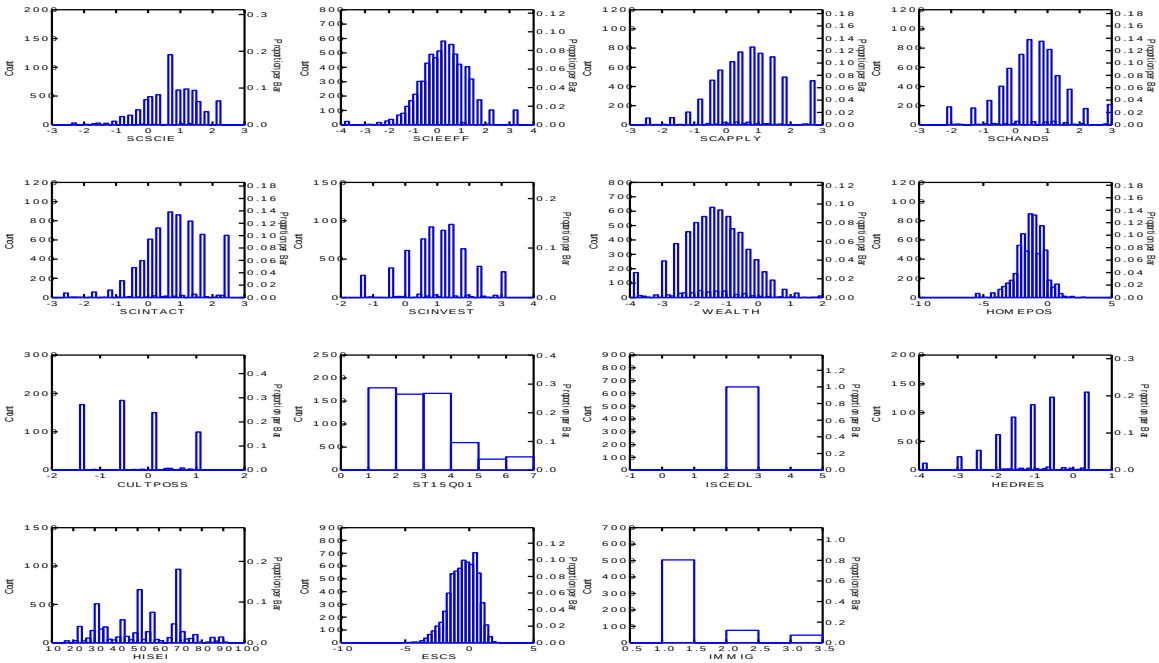

Figure B29. Jordan.

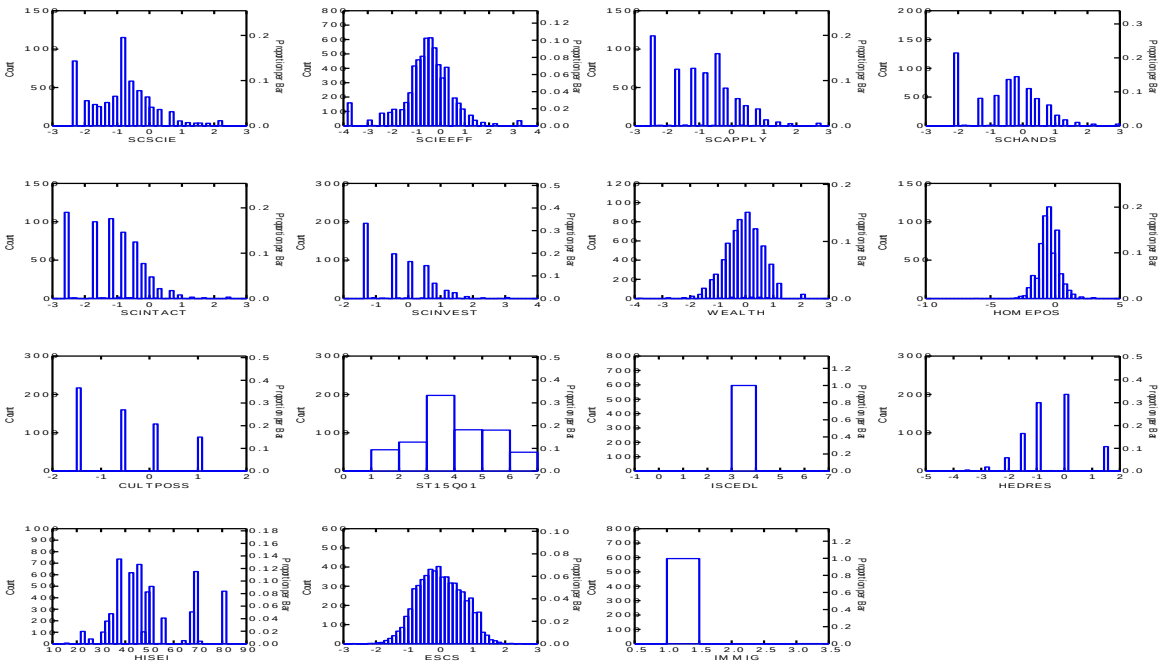

Figure B30. Japan.

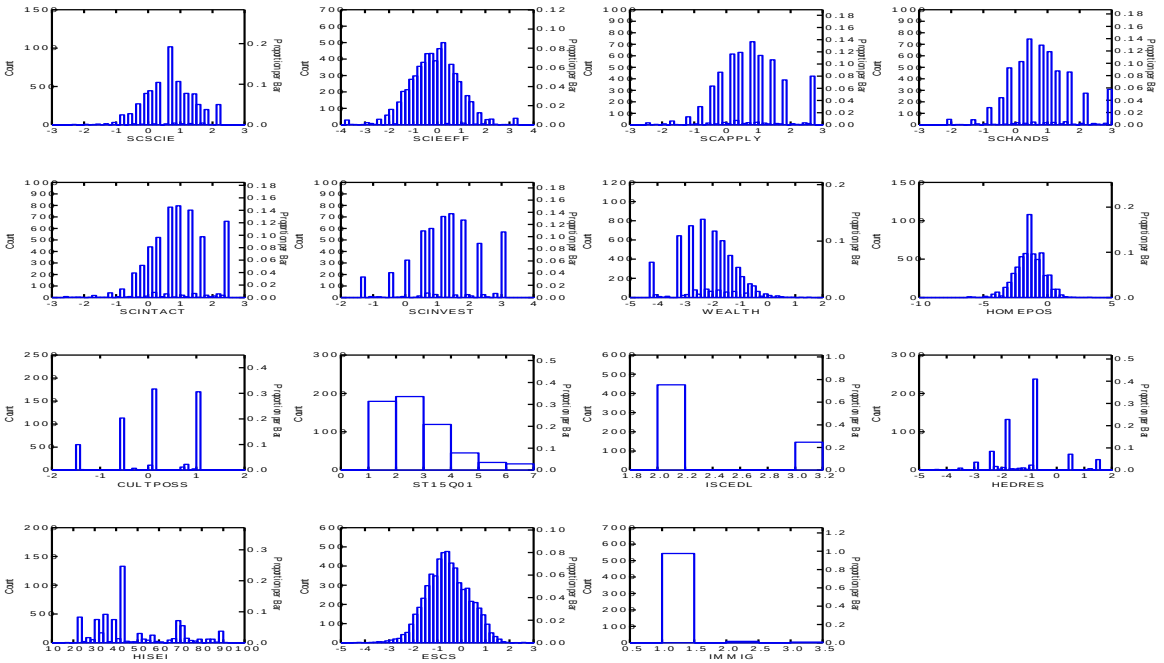

Figure B31. Kyrgystan.

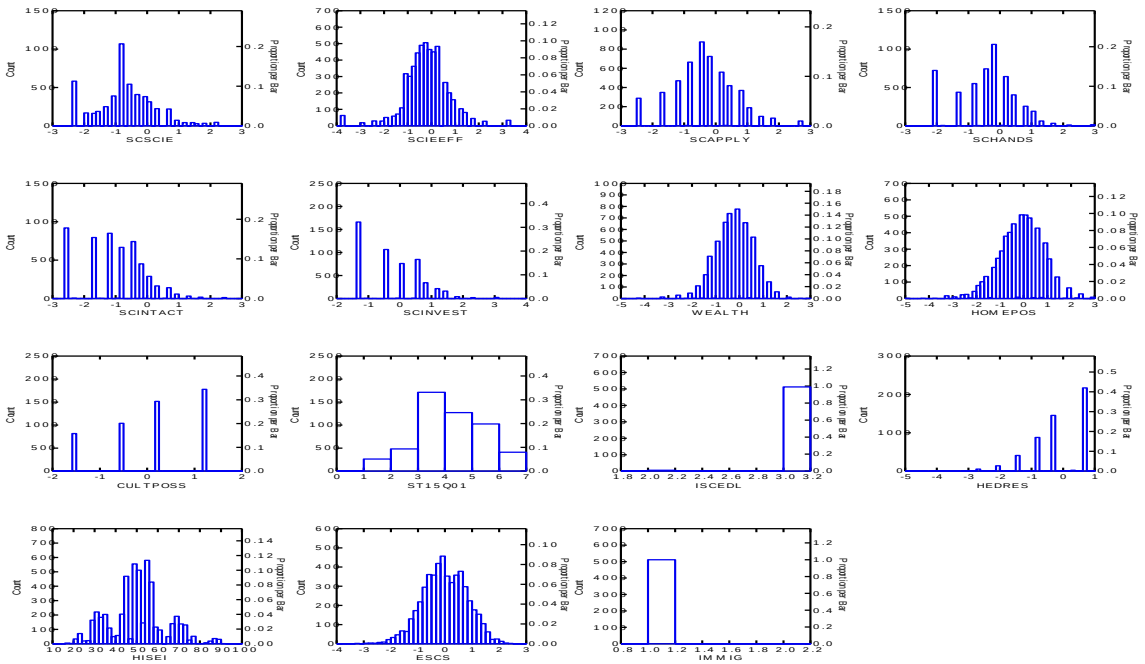

Figure B32. Korea.

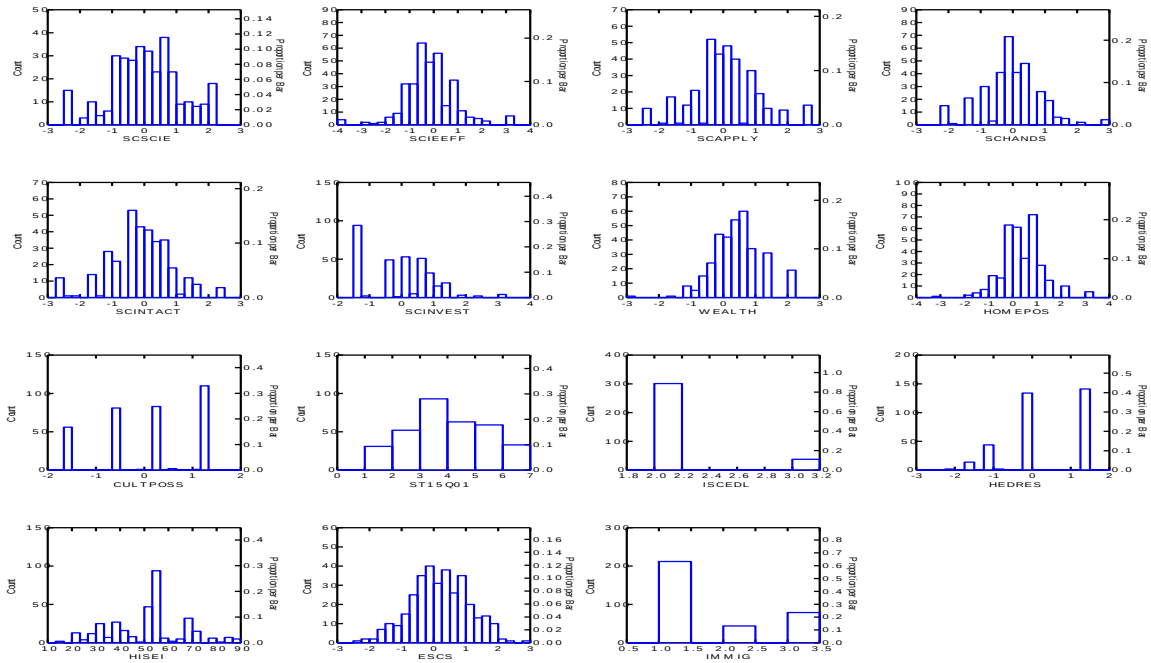

Figure B33. Liechtenstein.

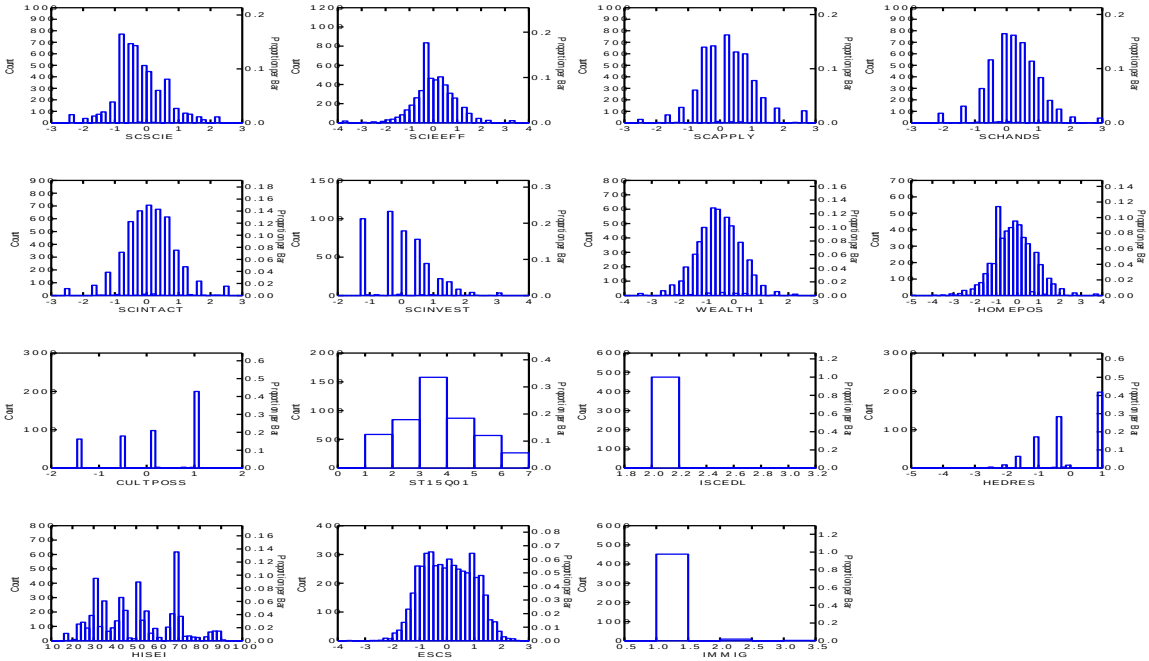

Figure B34. Lithuania.

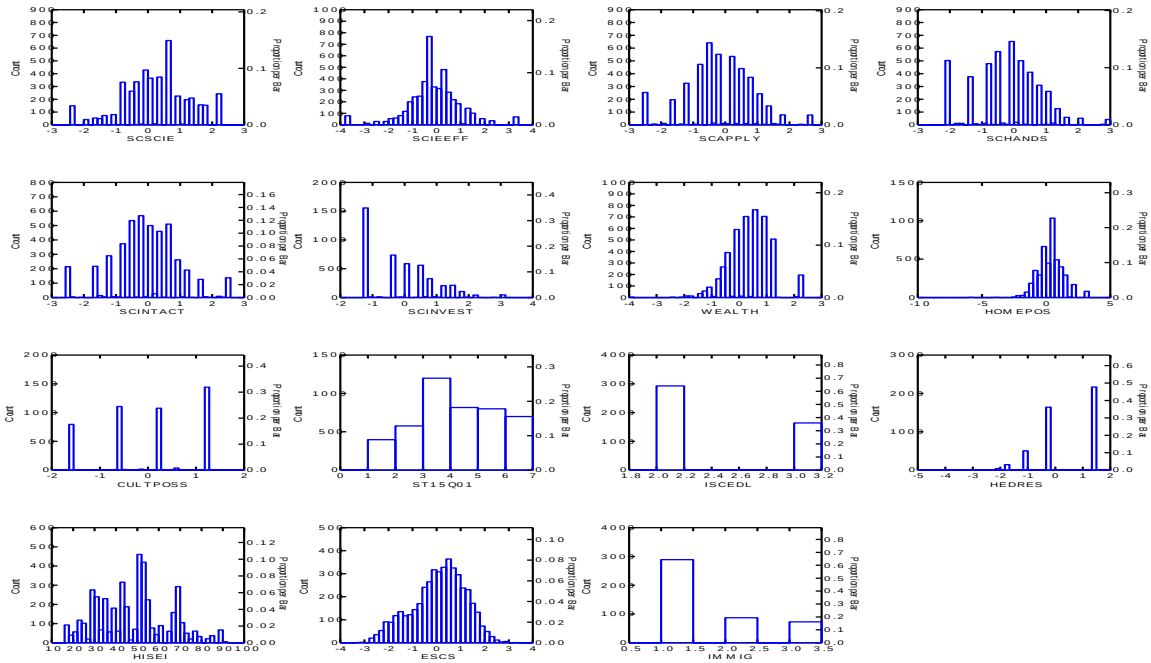

Figure B35. Luxembourg.

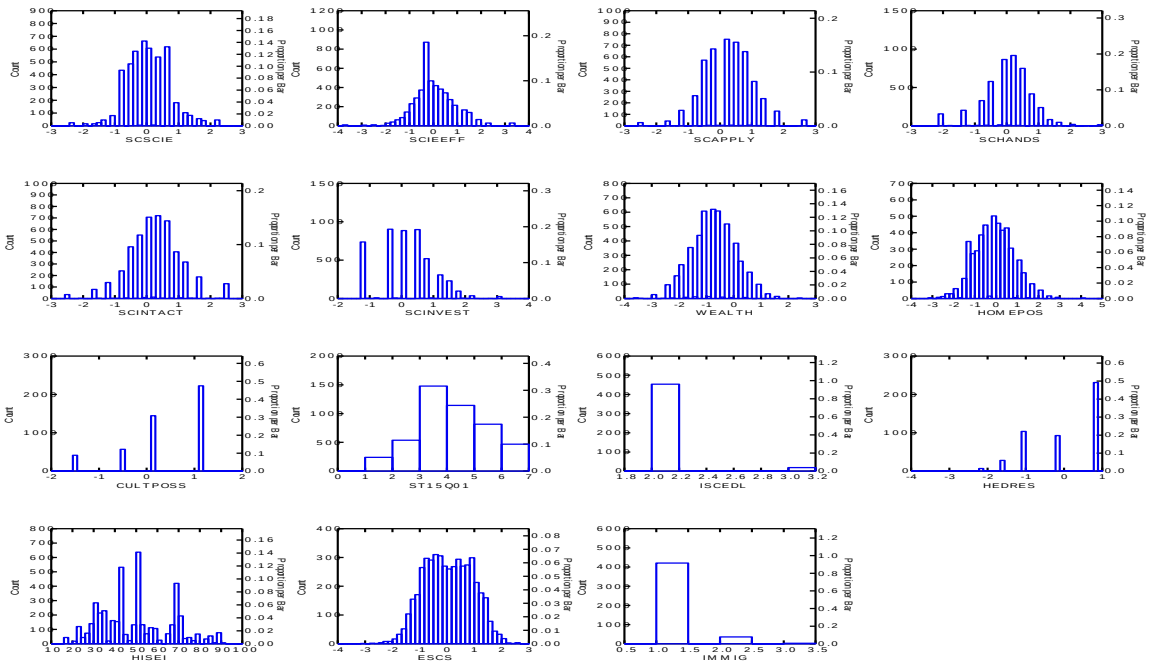

Figure B36. Latvia.

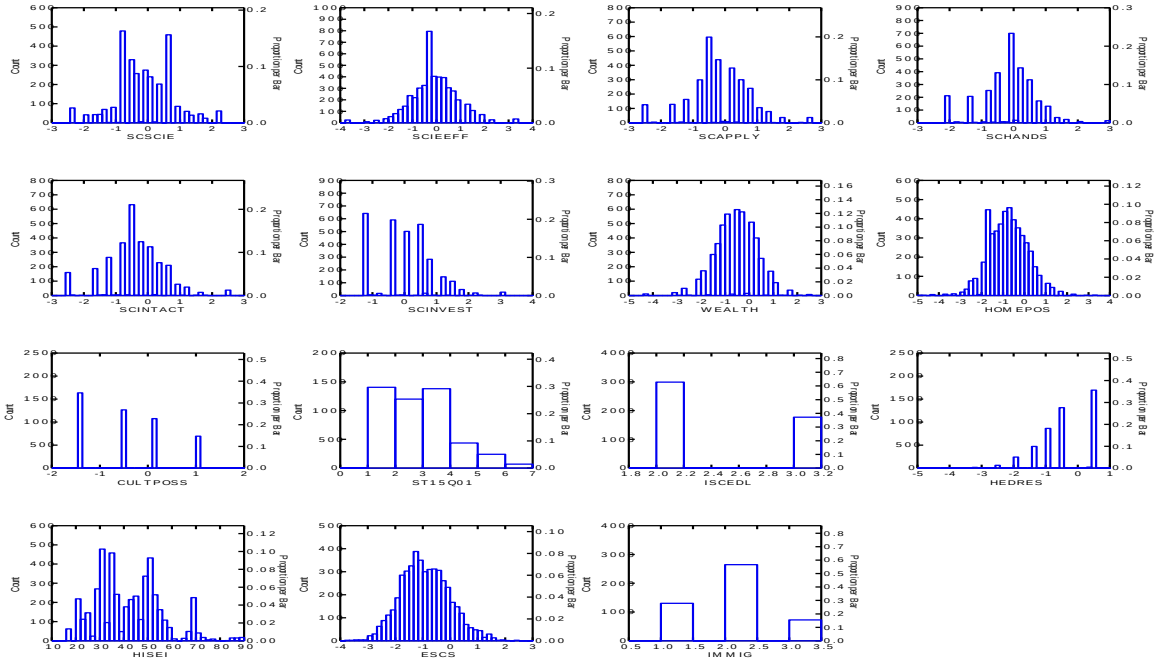

Figure B37. Macao-China.

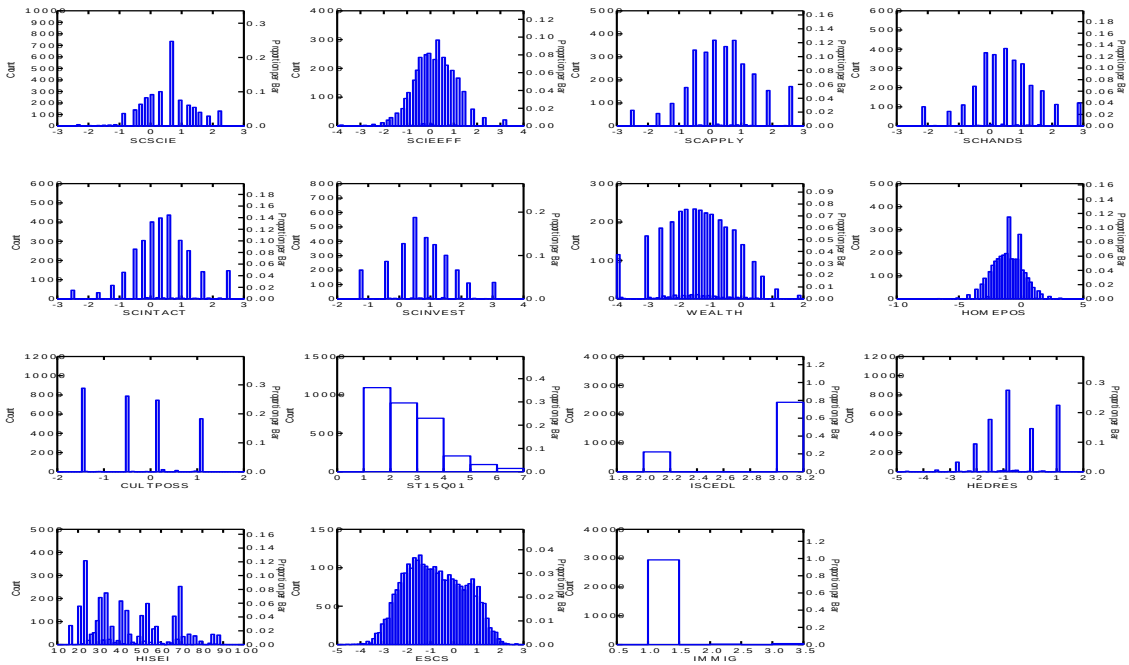

Figure B38. Mexico.

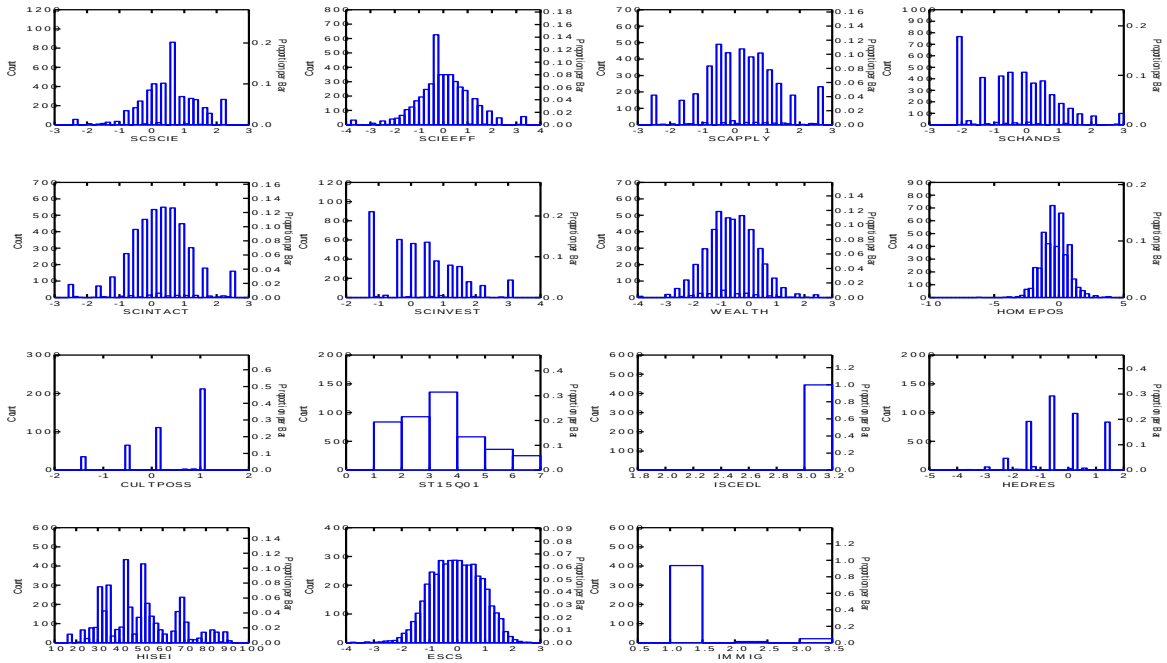

Figure B39. Montenegro.

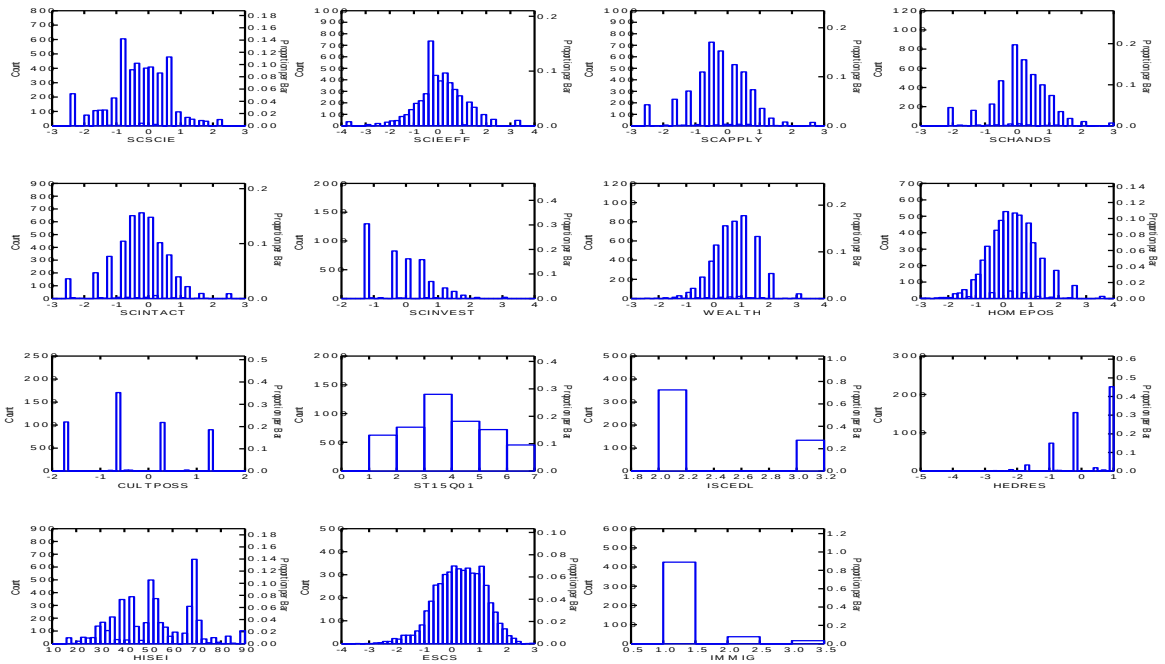

Figure B40. Netherlands.

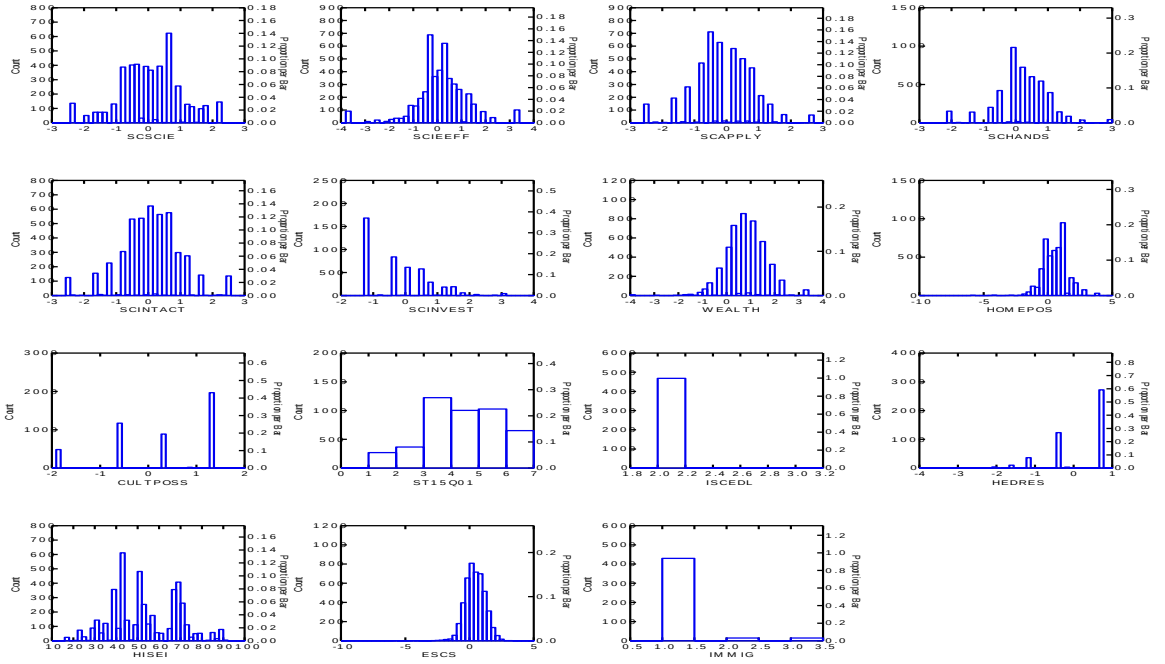

Figure B41. Norway.

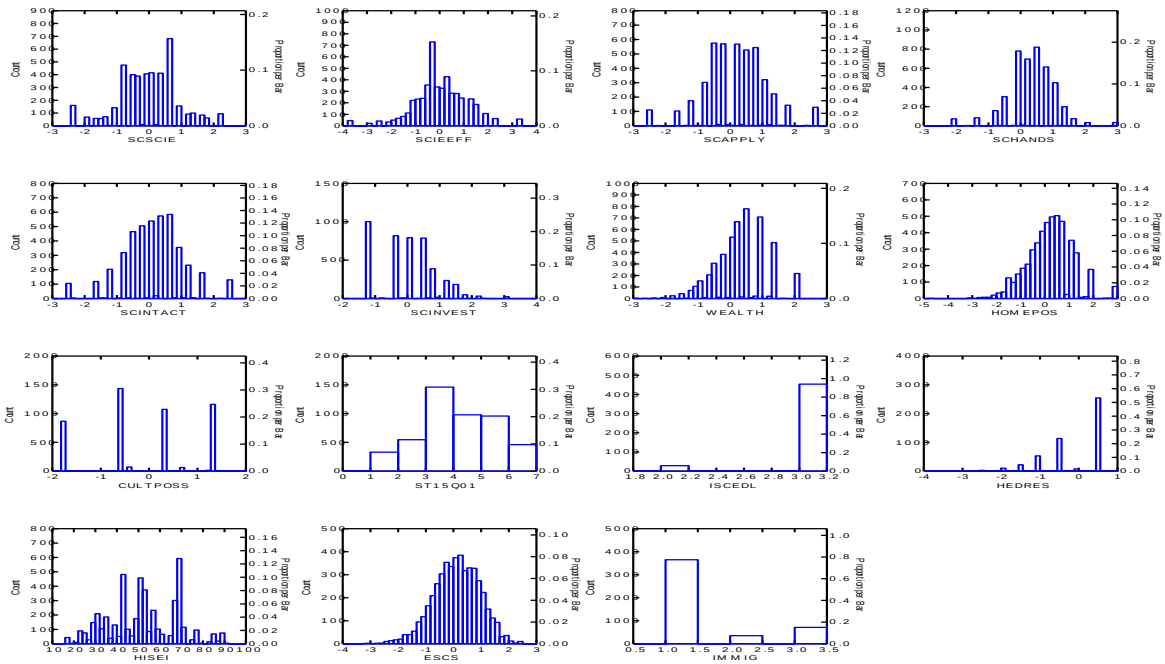

Figure B42. New Zealand.

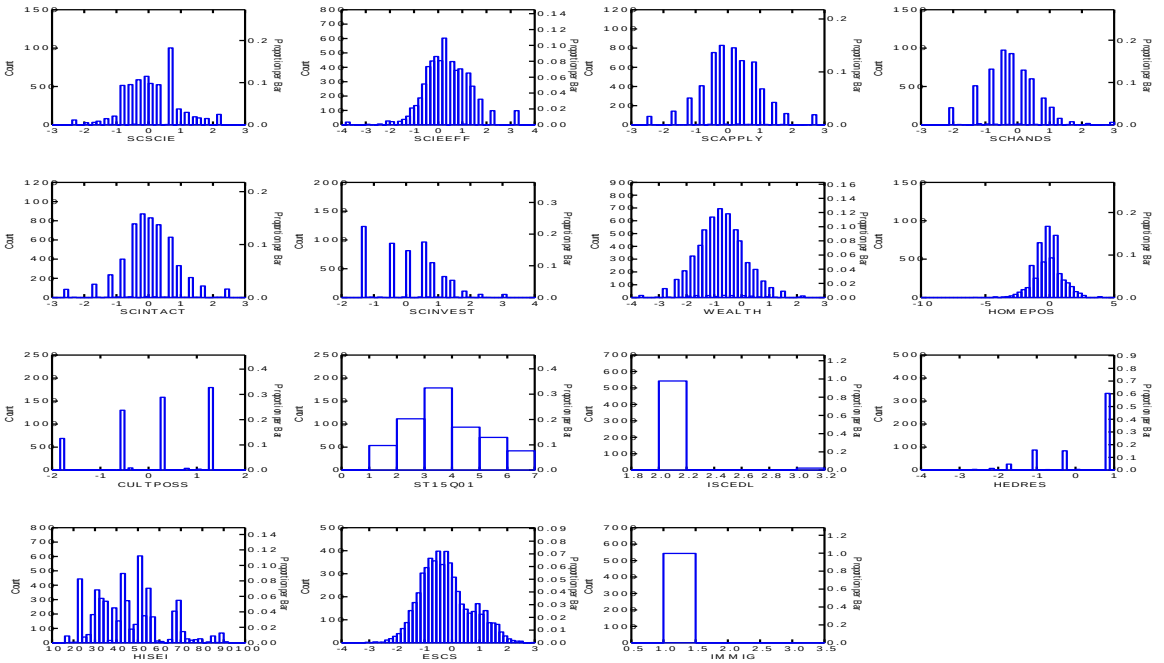

Figure B43. Poland.

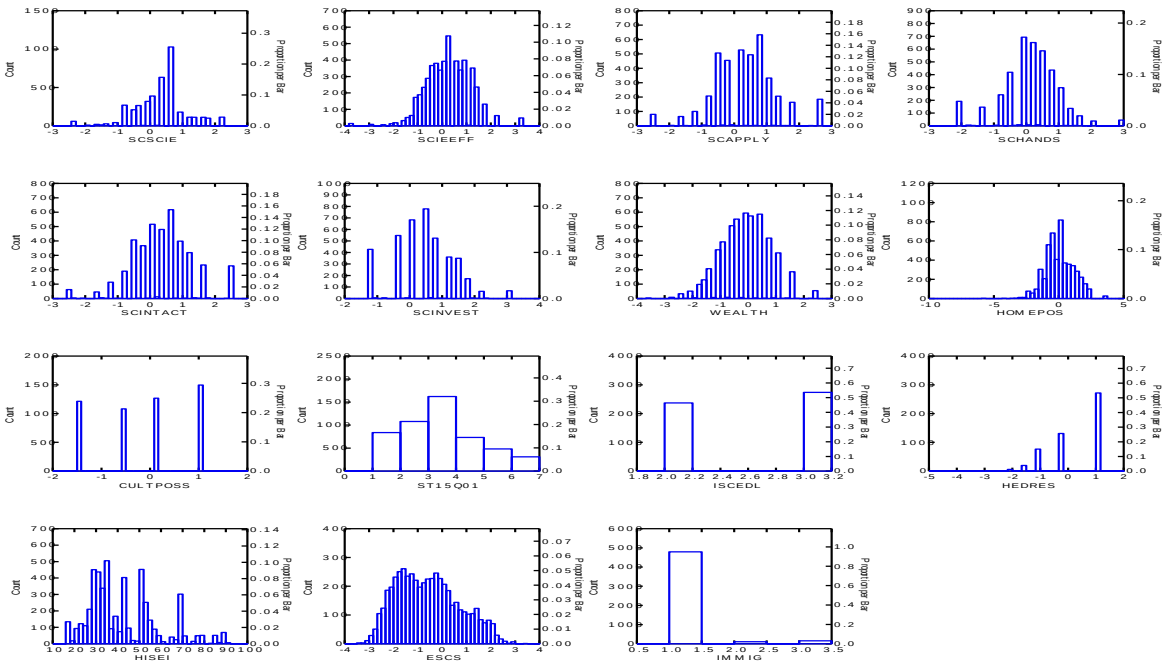

Figure B44. Portugal.

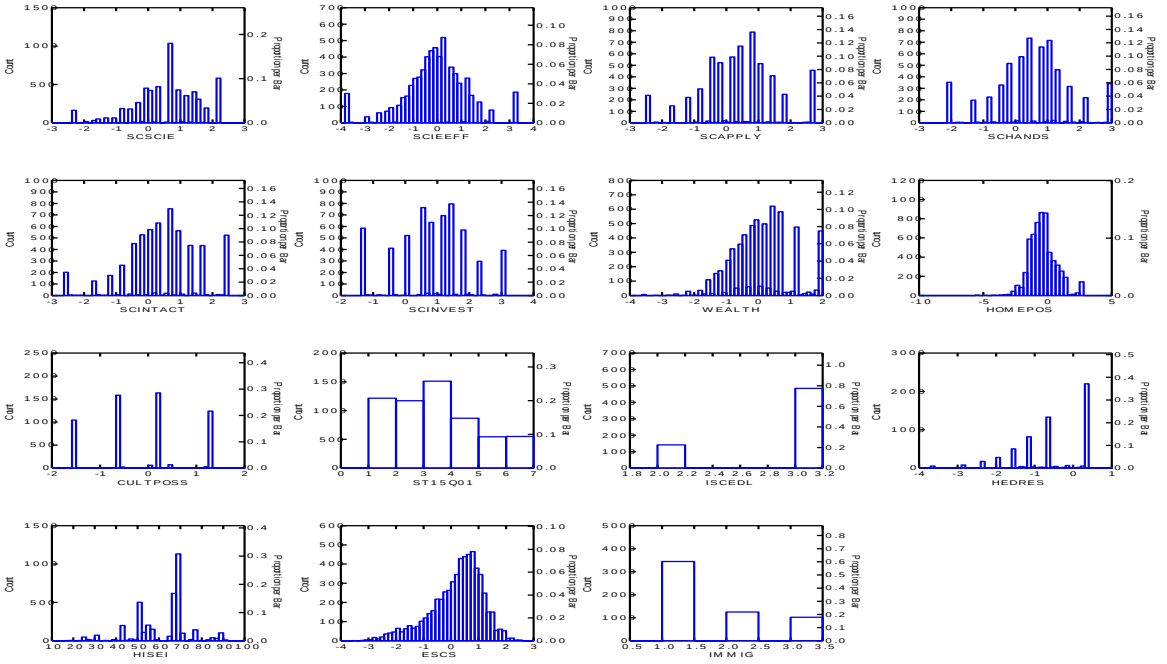

Figure B45. Qatar.

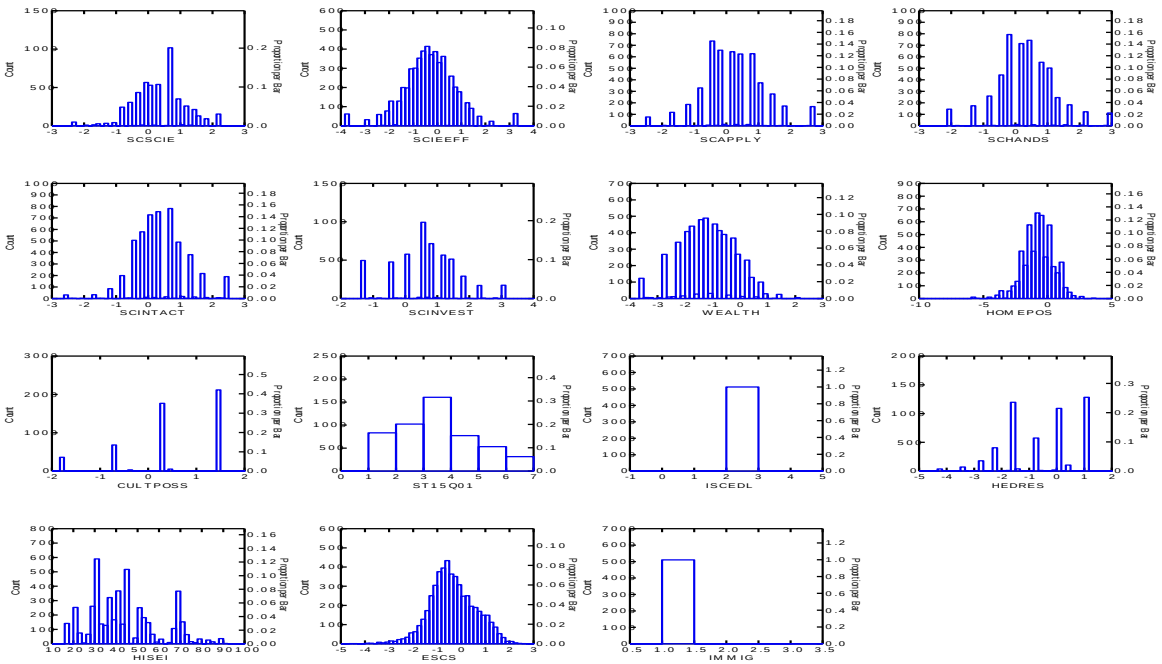

Figure B46. Romania.

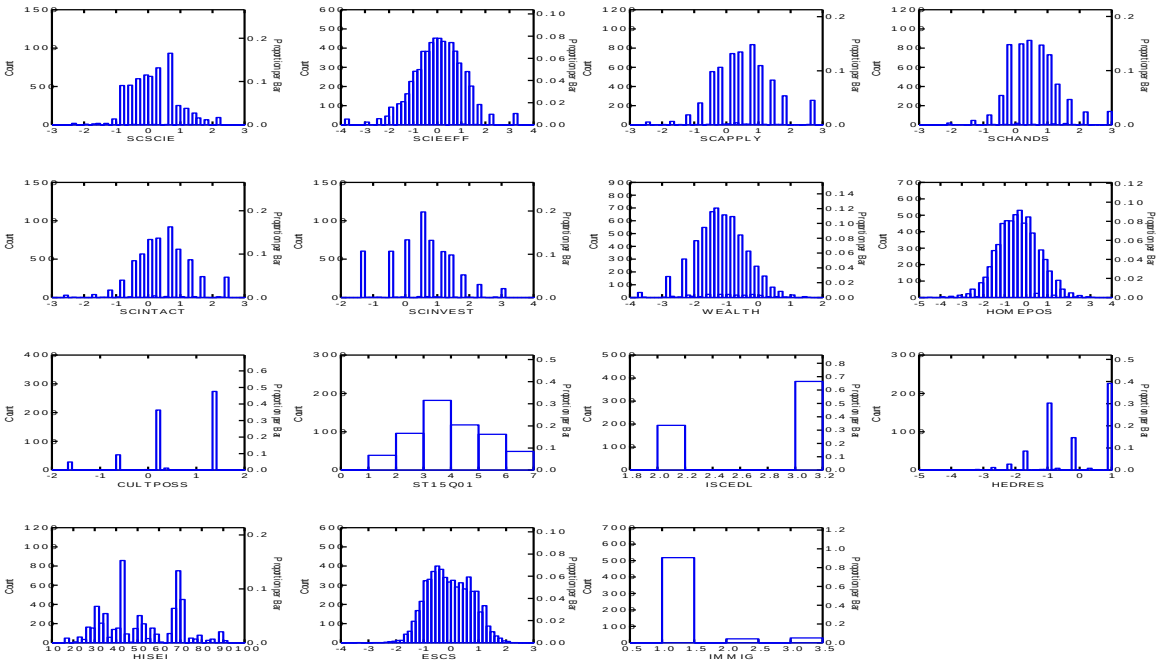

Figure B47. Russia Federation.

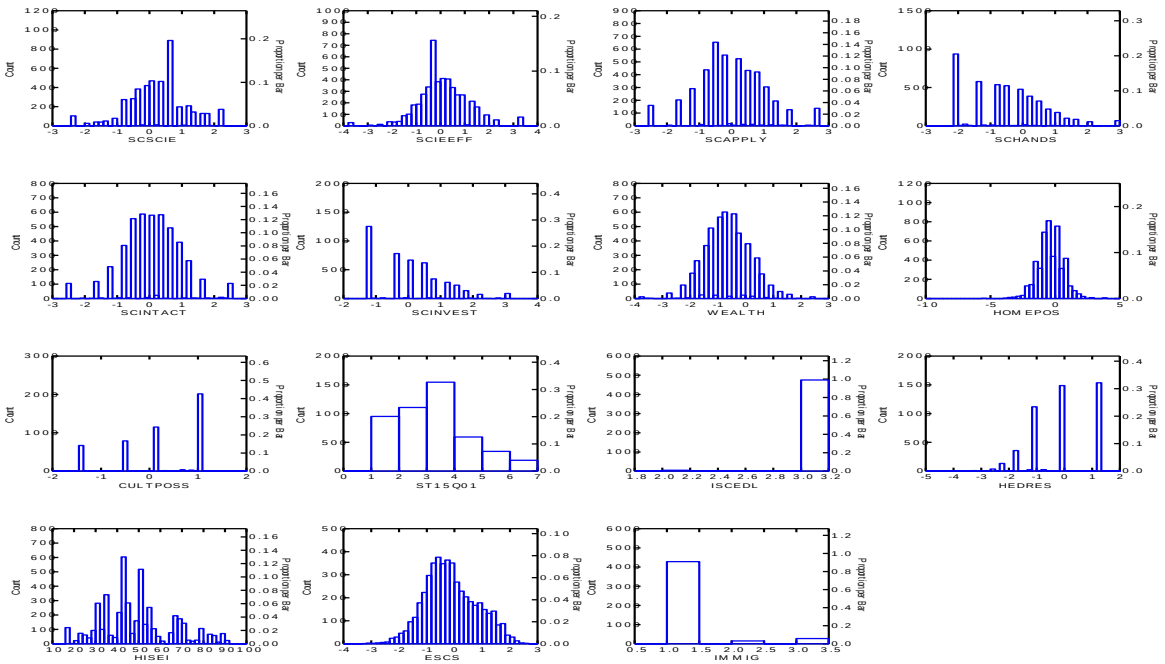

Figure B48. Serbia.

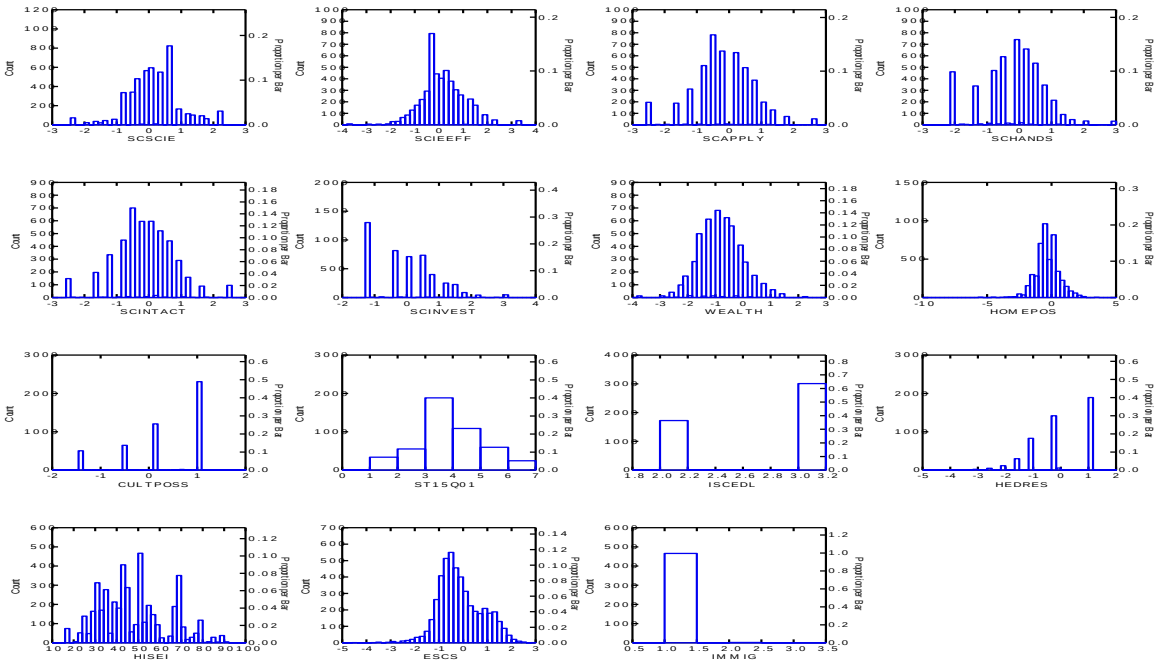

Figure B49. Slovak Republic.

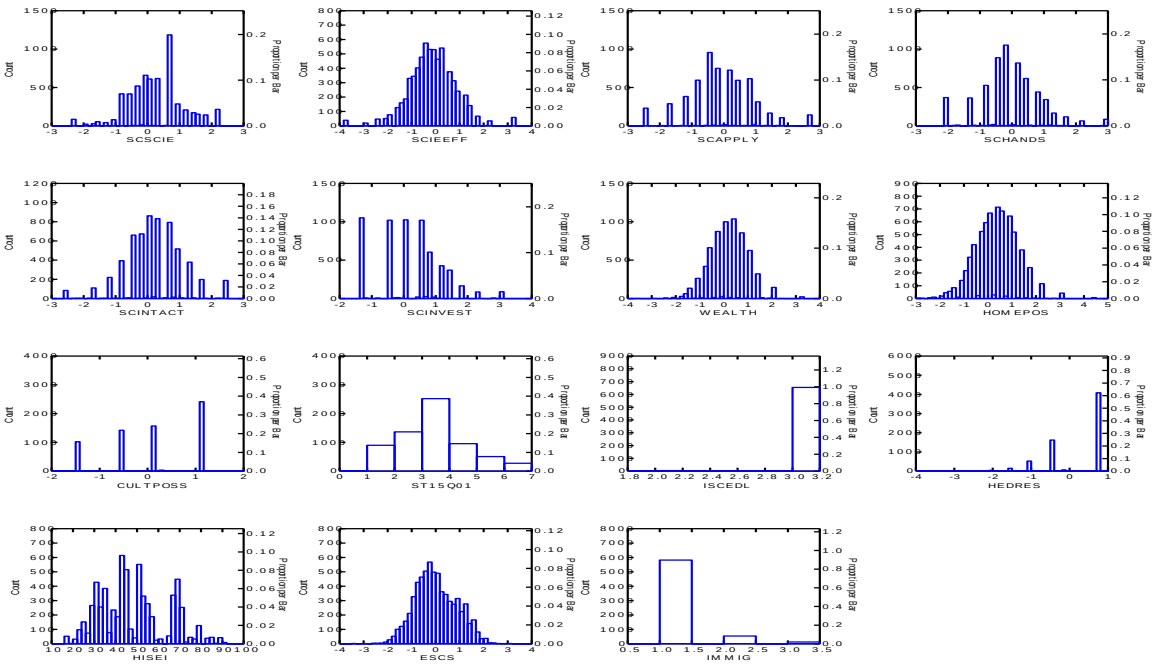

Figure B50. Slovenia.

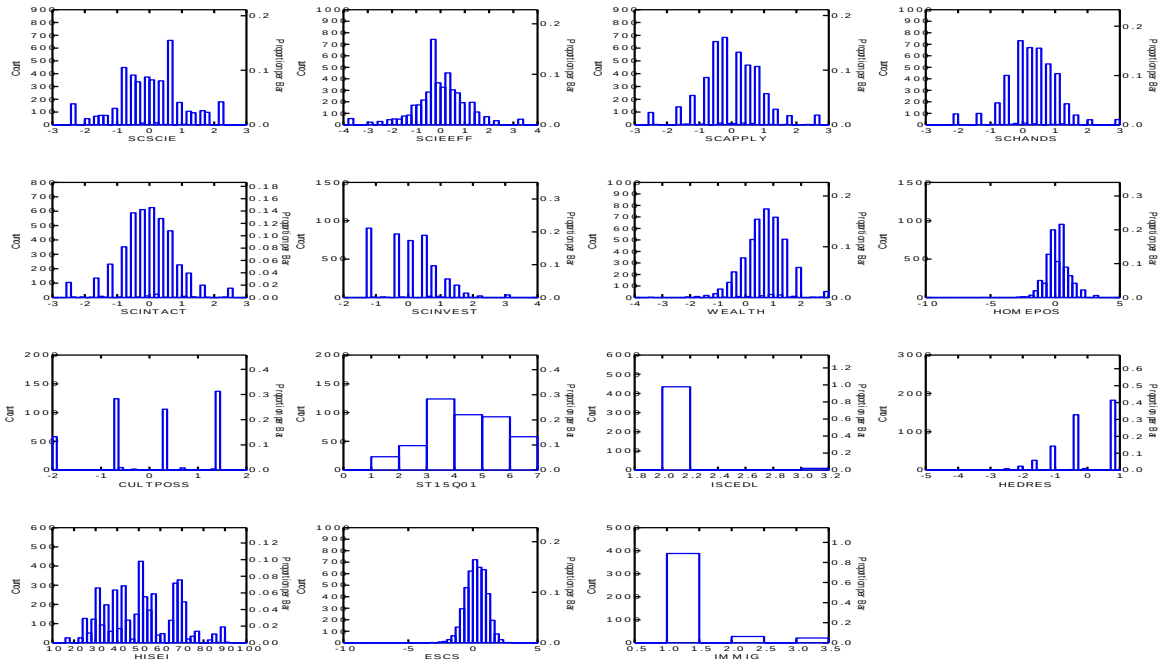

Figure B51. Sweden.

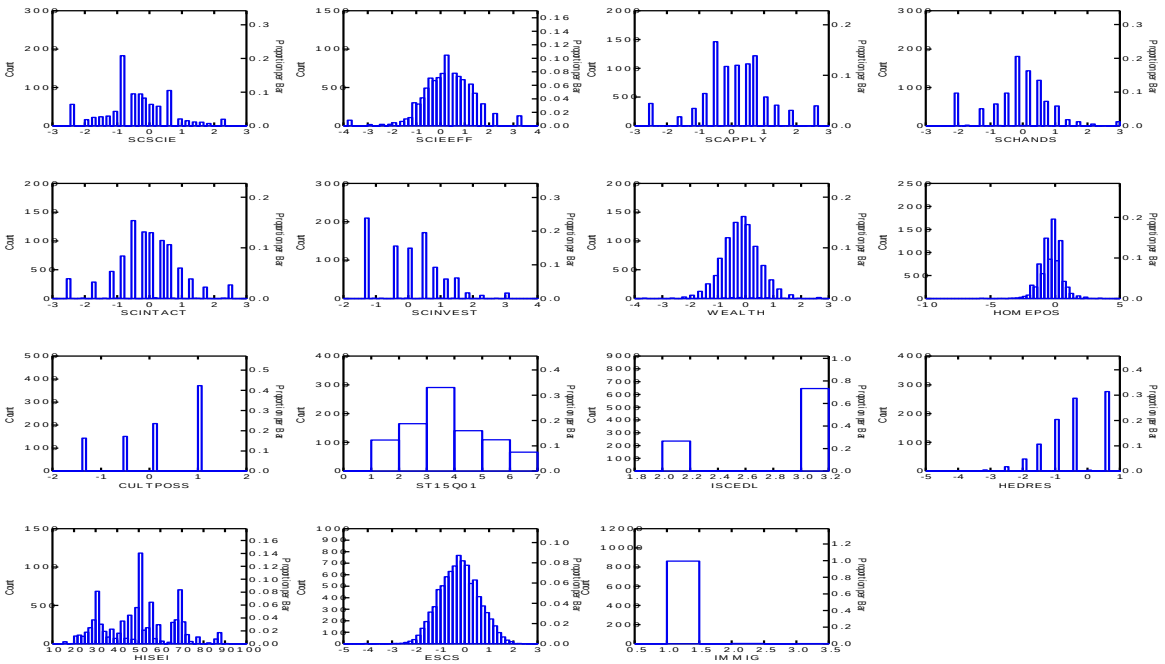

Figure B52. Chinese Taipei.

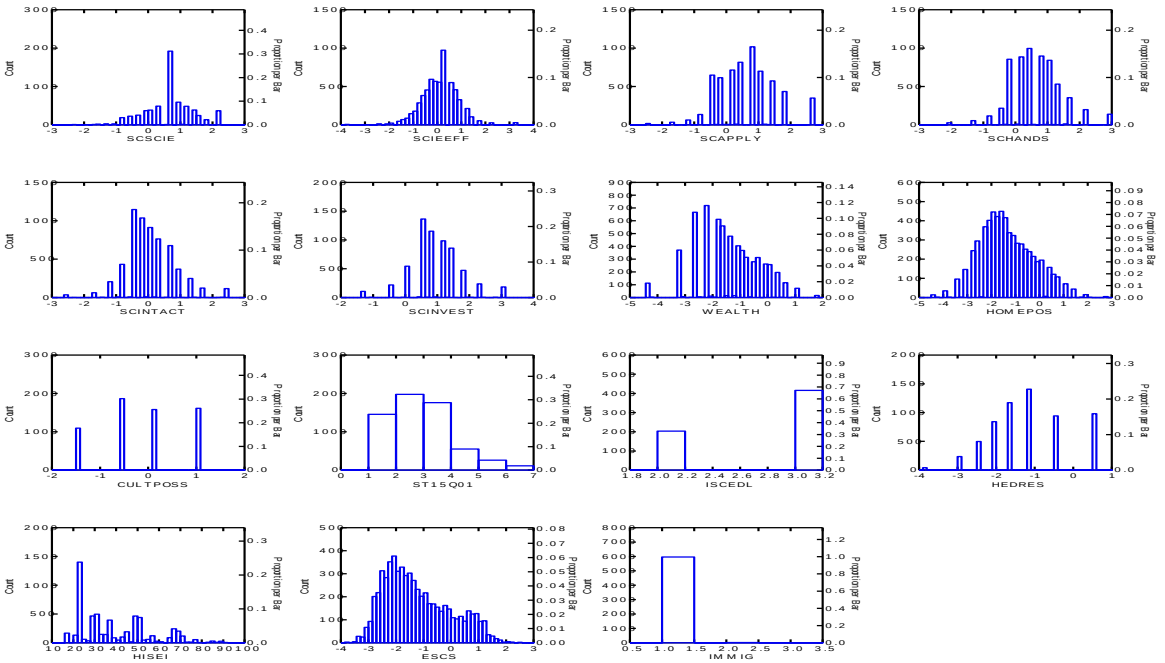

Figure B53. Thailand.

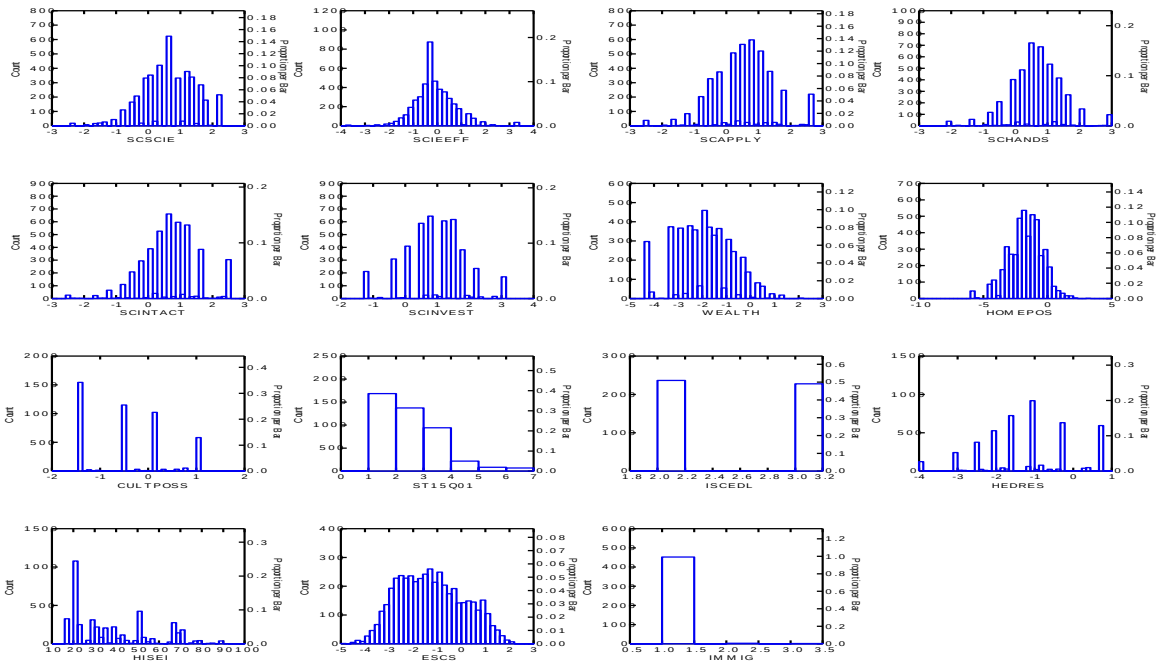

Figure B54. Tunisia.

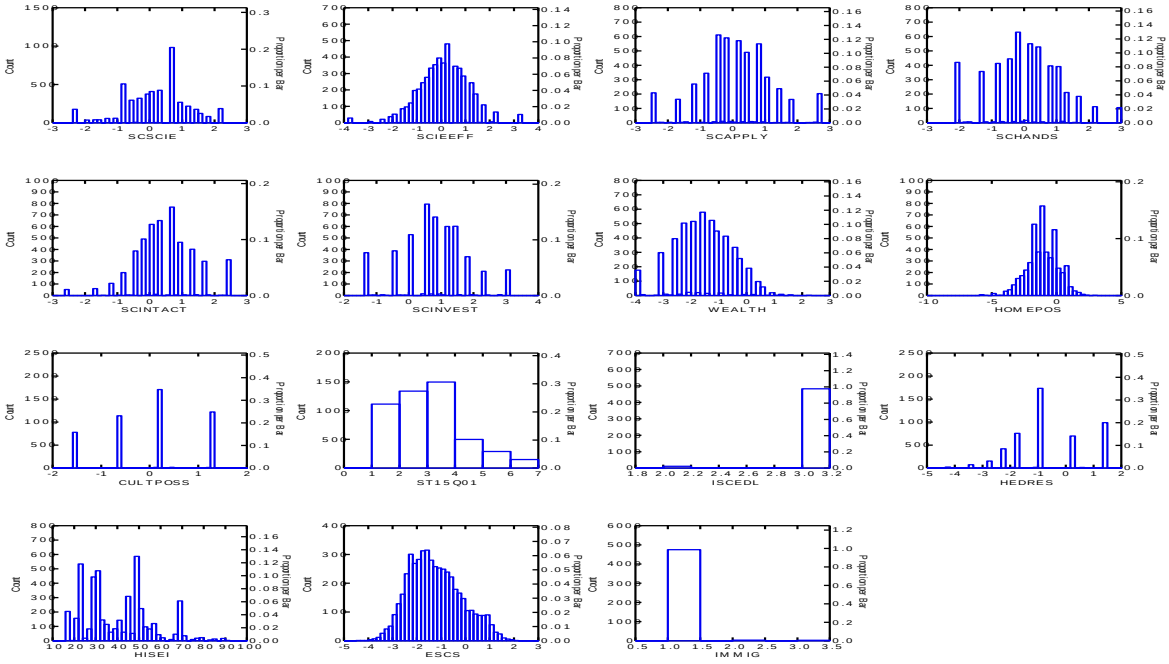

Figure B55. Turkey.

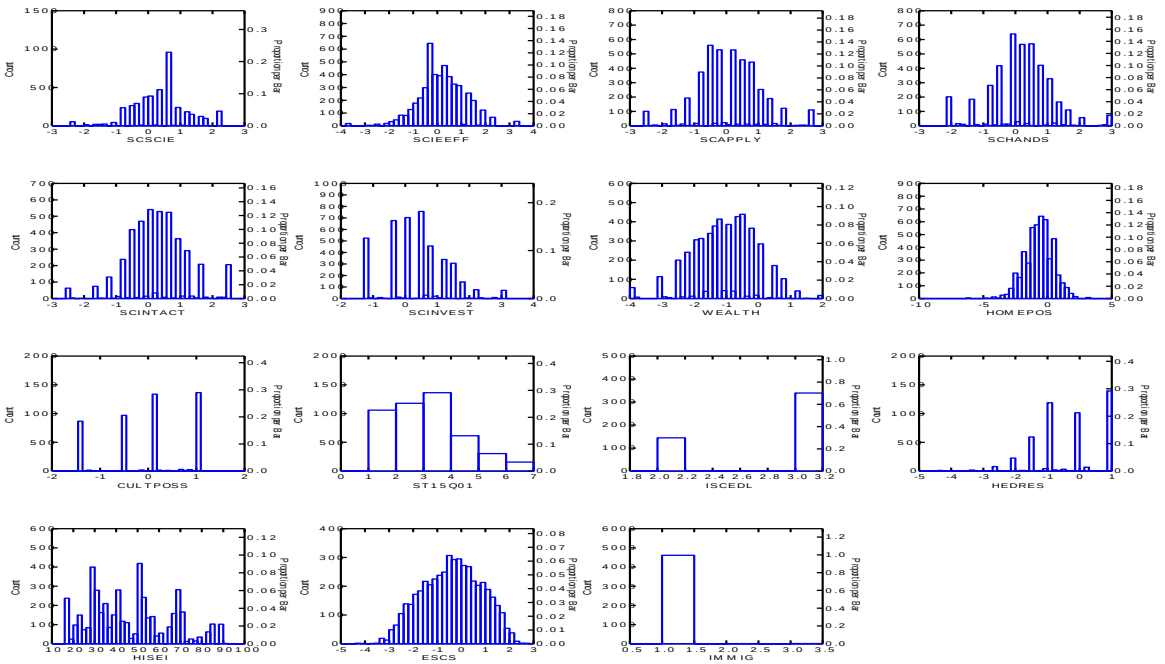

Figure B56. Uruguay.

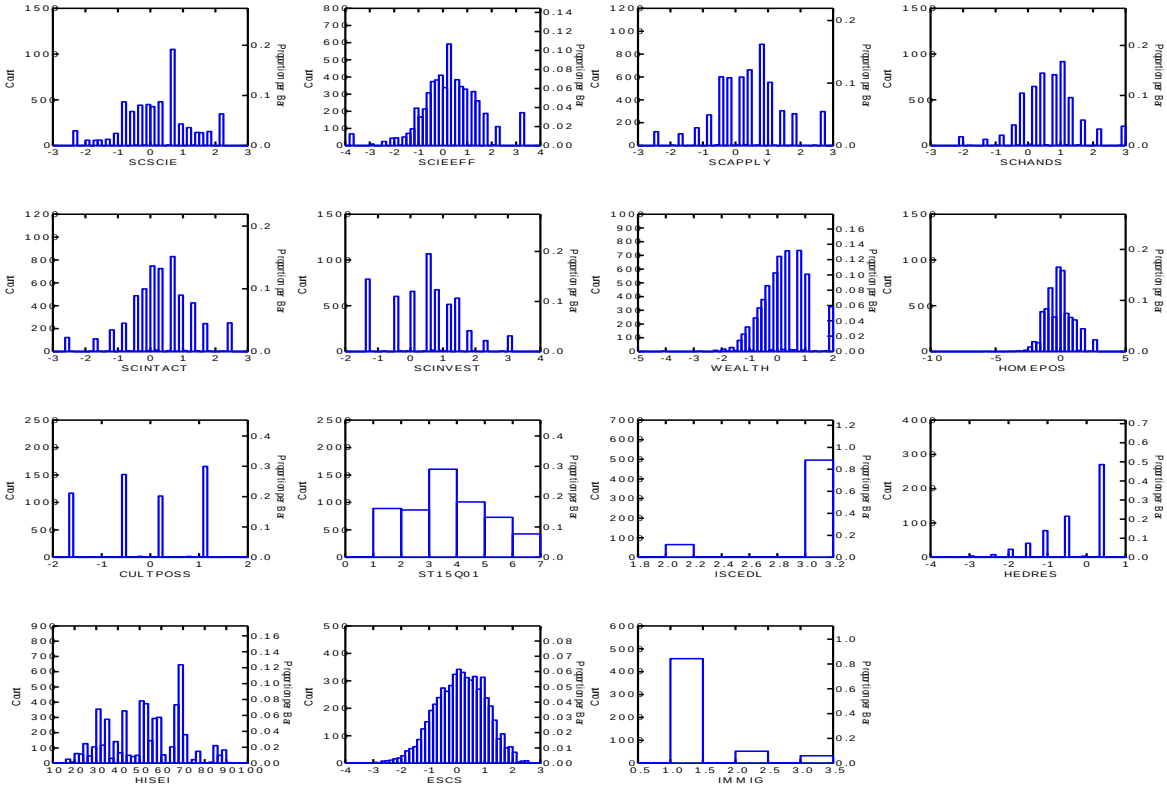

Figure B57. United States.

Appendix C: Descriptive Statistics for Science Plausible Values and Science Self-concept; Science Self-efficacy; Science - Focus on Application; Science - Hands on Activities; Science - Interactions; Science – Investigations; Wealth; Home Possessions; Cultural Possessions; Books in the Home (ST15Q01); ISCEDL; HEDRES; HISEI; ESCS; IMMIG All Countries

Table C1 - Azerbaijan

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4695	5025	4723	4759	4812
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.635	-0.427	0.649	0.534	0.754
Standard Dev	0.909	1.169	0.974	1.068	0.856
Skewness(G1)	-0.365	-0.086	0.048	-0.109	-0.002
SE Skewness	0.036	0.035	0.036	0.035	0.035
Kurtosis(G2)	0.157	1.355	0.255	0.300	0.405
SE Kurtosis	0.071	0.069	0.071	0.071	0.071

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4731	5156	5166	4941	4939
Minimum	-1.259	-3.752	-5.864	-1.463	1.000
Maximum	3.027	1.794	3.604	1.125	6.000
Mean	1.233	-1.994	-1.274	0.514	2.412
Standard Dev	0.971	1.008	1.189	0.776	1.334
Skewness(G1)	-0.212	0.172	-0.007	-1.038	0.915
SE Skewness	0.036	0.034	0.034	0.035	0.035
Kurtosis(G2)	0.245	-0.147	0.505	0.100	0.312
SE Kurtosis	0.071	0.068	0.068	0.070	0.070

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	5184	5076	4362	5150	4851
Minimum	2.000	-4.484	16.000	-4.597	1.000
Maximum	3.000	1.502	90.000	2.738	3.000
Mean	2.418	-1.247	50.324	-0.387	1.037
Standard Dev	0.493	1.242	18.713	1.071	0.240
Skewness(G1)	0.332	0.489	0.196	0.092	6.941
SE Skewness	0.034	0.034	0.037	0.034	0.035
Kurtosis(G2)	-1.891	0.213	-1.112	-0.512	49.609
SE Kurtosis	0.068	0.069	0.074	0.068	0.070

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	5184	5184	5184	5184	5184
Minimum	215.812	228.307	204.342	222.992	220.194
Maximum	608.850	608.850	610.248	651.277	595.329
Mean	385.347	385.385	385.626	385.001	385.373
Standard Dev	56.715	57.216	56.539	57.145	56.723
Skewness(G1)	0.495	0.508	0.528	0.471	0.485
SE Skewness	0.034	0.034	0.034	0.034	0.034
Kurtosis(G2)	0.271	0.368	0.385	0.300	0.298
SE Kurtosis	0.068	0.068	0.068	0.068	0.068

Table C2 - Argentina

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	3980	4272	4031	4055	4065
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.274	-0.028	0.078	-0.166	0.332
Standard Dev	0.884	0.913	1.085	1.086	0.948
Skewness(G1)	-0.060	-0.075	0.054	0.151	0.026
SE Skewness	0.039	0.037	0.039	0.038	0.038

Kurtosis(G2)	0.331	1.779	0.211	0.066	0.557
SE Kurtosis	0.078	0.075	0.077	0.077	0.077

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4027	4301	4304	4176	4240
Minimum	-1.259	-4.128	-6.055	-1.480	1.000
Maximum	3.027	1.801	3.068	1.101	6.000
Mean	0.337	-1.309	-1.047	-0.213	2.367
Standard Dev	1.042	0.897	1.014	0.881	1.252
Skewness(G1)	0.244	-0.182	-0.151	0.006	0.831
SE Skewness	0.039	0.037	0.037	0.038	0.038
Kurtosis(G2)	-0.215	0.173	0.404	-1.047	0.261
SE Kurtosis	0.077	0.075	0.075	0.076	0.075

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4339	4280	4036	4292	4264
Minimum	2.000	-4.319	16.000	-4.215	1.000
Maximum	3.000	0.870	90.000	2.930	3.000
Mean	2.710	-0.686	45.982	-0.608	1.040
Standard Dev	0.454	1.058	16.945	1.140	0.248
Skewness(G1)	-0.928	-0.004	0.438	-0.062	6.691
SE Skewness	0.037	0.037	0.039	0.037	0.037
Kurtosis(G2)	-1.140	-0.472	-0.571	-0.555	46.079
SE Kurtosis	0.074	0.075	0.077	0.075	0.075

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4339	4339	4339	4339	4339
Minimum	66.616	45.635	49.552	48.619	61.021
Maximum	744.898	703.869	746.763	714.312	675.149
Mean	398.912	397.835	397.621	398.842	398.424
Standard Dev	96.627	96.008	97.223	96.678	96.554
Skewness(G1)	-0.088	-0.104	-0.130	-0.126	-0.131
SE Skewness	0.037	0.037	0.037	0.037	0.037
Kurtosis(G2)	-0.068	-0.094	0.025	-0.009	-0.056
SE Kurtosis	0.074	0.074	0.074	0.074	0.074

Table C3 - Australia

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	11738	14064	11787	11818	11825
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	-0.047	0.098	0.211	0.385	0.177
Standard Dev	0.990	1.113	0.973	0.778	0.955
Skewness(G1)	-0.127	-0.140	-0.066	-0.276	-0.107
SE Skewness	0.023	0.021	0.023	0.023	0.023
Kurtosis(G2)	0.286	1.832	0.806	1.970	0.760
SE Kurtosis	0.045	0.041	0.045	0.045	0.045

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	11788	14091	14091	13841	13935
Minimum	-1.259	-3.830	-5.838	-1.736	1.000
Maximum	3.027	2.333	3.113	1.247	6.000
Mean	0.184	0.380	0.170	-0.125	3.679
Standard Dev	0.916	0.727	0.852	1.042	1.390
Skewness(G1)	0.097	0.118	0.161	-0.114	-0.064
SE Skewness	0.023	0.021	0.021	0.021	0.021
Kurtosis(G2)	-0.063	0.604	1.431	-1.119	-0.702
SE Kurtosis	0.045	0.041	0.041	0.042	0.041

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	14170	14014	13646	13995	13844
Minimum	2.000	-4.010	16.000	-3.902	1.000

Maximum	3.000	0.614	90.000	2.536	3.000
Mean	2.189	0.008	52.975	0.191	1.278
Standard Dev	0.391	0.825	16.401	0.784	0.603
Skewness(G1)	1.591	-1.352	-0.097	-0.241	2.014
SE Skewness	0.021	0.021	0.021	0.021	0.021
Kurtosis(G2)	0.531	1.815	-0.687	0.051	2.681
SE Kurtosis	0.041	0.041	0.042	0.041	0.042

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	14170	14170	14170	14170	14170
Minimum	71.838	85.732	129.092	123.963	116.690
Maximum	869.010	847.563	868.264	847.563	873.859
Mean	523.024	523.074	523.103	522.977	523.476
Standard Dev	102.979	103.017	103.119	102.719	103.286
Skewness(G1)	-0.206	-0.220	-0.205	-0.194	-0.200
SE Skewness	0.021	0.021	0.021	0.021	0.021
Kurtosis(G2)	-0.075	-0.130	-0.122	-0.174	-0.162
SE Kurtosis	0.041	0.041	0.041	0.041	0.041

Table C4 - Austria

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4278	4885	4270	4292	4299
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.080	-0.107	-0.097	-0.431	0.156
Standard Dev	1.091	0.964	1.021	1.083	1.091
Skewness(G1)	-0.071	-0.150	-0.095	0.176	-0.116
SE Skewness	0.037	0.035	0.037	0.037	0.037
Kurtosis(G2)	-0.390	2.003	0.427	-0.192	0.261
SE Kurtosis	0.075	0.070	0.075	0.075	0.075

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4269	4919	4920	4865	4898
Minimum	-1.259	-2.515	-2.588	-1.532	1.000
Maximum	3.027	2.158	3.203	1.213	6.000
Mean	-0.261	0.170	0.278	0.078	3.392
Standard Dev	1.009	0.747	0.832	0.961	1.378
Skewness(G1)	0.735	0.130	0.307	-0.244	0.191
SE Skewness	0.037	0.035	0.035	0.035	0.035
Kurtosis(G2)	-0.076	0.207	0.722	-1.120	-0.624
SE Kurtosis	0.075	0.070	0.070	0.070	0.070

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4927	4904	4790	4914	4891
Minimum	2.000	-3.360	16.000	-2.899	1.000
Maximum	3.000	1.492	90.000	2.840	3.000
Mean	2.957	0.473	48.134	0.198	1.202
Standard Dev	0.202	1.016	16.600	0.822	0.559
Skewness(G1)	-4.518	-0.528	0.376	0.139	2.627
SE Skewness	0.035	0.035	0.035	0.035	0.035
Kurtosis(G2)	18.415	-0.678	-0.436	0.108	5.336
SE Kurtosis	0.070	0.070	0.071	0.070	0.070

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4927	4927	4927	4927	4927
Minimum	158.651	140.934	184.481	136.272	153.989
Maximum	816.791	790.962	798.422	835.721	808.679
Mean	513.843	514.043	514.428	513.765	513.244
Standard Dev	95.356	95.943	95.661	95.768	96.429
Skewness(G1)	-0.186	-0.199	-0.215	-0.171	-0.188
SE Skewness	0.035	0.035	0.035	0.035	0.035
Kurtosis(G2)	-0.246	-0.305	-0.265	-0.292	-0.288

SE Kurtosis	0.070	0.070	0.070	0.070	0.070

Table C5 - Belgium

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	7525	8637	7533	7570	7588
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	-0.145	-0.088	-0.157	-0.334	-0.144
Standard Dev	0.982	0.998	0.987	0.946	0.952
Skewness(G1)	-0.152	-0.405	-0.209	0.020	-0.094
SE Skewness	0.028	0.026	0.028	0.028	0.028
Kurtosis(G2)	0.221	2.016	0.508	0.121	0.672
SE Kurtosis	0.056	0.053	0.056	0.056	0.056

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	7532	8838	8842	8666	8748
Minimum	-1.259	-3.564	-4.631	-1.604	1.000
Maximum	3.027	2.825	3.591	1.168	6.000
Mean	-0.353	0.192	0.114	-0.238	3.283
Standard Dev	0.951	0.777	0.816	0.956	1.447
Skewness(G1)	0.768	0.199	0.109	0.052	0.179
SE Skewness	0.028	0.026	0.026	0.026	0.026
Kurtosis(G2)	-0.110	0.536	1.177	-1.198	-0.767
SE Kurtosis	0.056	0.052	0.052	0.053	0.052

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	8857	8828	8543	8777	8743
Minimum	2.000	-3.972	16.000	-4.442	1.000
Maximum	3.000	1.235	90.000	2.995	3.000
Mean	2.943	0.139	50.141	0.195	1.189
Standard Dev	0.233	0.843	16.578	0.901	0.533
Skewness(G1)	-3.808	-0.666	0.173	-0.214	2.726
SE Skewness	0.026	0.026	0.026	0.026	0.026
Kurtosis(G2)	12.504	0.072	-0.679	0.130	6.026
SE Kurtosis	0.052	0.052	0.053	0.052	0.052

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	8857	8857	8857	8857	8857
Minimum	125.176	143.825	131.609	138.230	149.140
Maximum	841.129	833.483	791.615	813.248	816.978
Mean	516.211	516.380	516.307	516.475	516.211
Standard Dev	96.929	97.020	97.528	97.380	97.634
Skewness(G1)	-0.356	-0.305	-0.326	-0.322	-0.326
SE Skewness	0.026	0.026	0.026	0.026	0.026
Kurtosis(G2)	-0.199	-0.228	-0.213	-0.233	-0.258
SE Kurtosis	0.052	0.052	0.052	0.052	0.052

Table C6 - Brazil

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	8661	9170	8761	8798	8832
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.395	-0.042	0.266	-0.240	0.146
Standard Dev	0.831	0.941	1.046	1.048	0.934
Skewness(G1)	0.052	-0.010	0.020	0.126	0.072
SE Skewness	0.026	0.026	0.026	0.026	0.026
Kurtosis(G2)	0.023	1.619	0.190	-0.050	0.505
SE Kurtosis	0.053	0.051	0.052	0.052	0.052

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	8763	9206	9215	9017	9019

Minimum	-1.259	-3.661	-5.886	-1.421	1.000
Maximum	3.027	1.895	3.025	1.052	6.000
Mean	0.525	-1.523	-1.350	-0.111	2.121
Standard Dev	1.034	0.949	1.030	0.821	1.138
Skewness(G1)	0.044	-0.022	-0.138	-0.139	1.058
SE Skewness	0.026	0.026	0.026	0.026	0.026
Kurtosis(G2)	-0.314	0.068	0.672	-0.930	0.989
SE Kurtosis	0.052	0.051	0.051	0.052	0.052

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	9295	9167	8767	9208	9053
Minimum	2.000	-4.435	16.000	-4.724	1.000
Maximum	3.000	0.909	90.000	2.687	3.000
Mean	2.594	-1.135	42.516	-1.030	1.029
Standard Dev	0.491	1.064	18.417	1.262	0.183
Skewness(G1)	-0.384	0.168	0.184	-0.032	6.795
SE Skewness	0.025	0.026	0.026	0.026	0.026
Kurtosis(G2)	-1.853	-0.073	-1.014	-0.913	50.589
SE Kurtosis	0.051	0.051	0.052	0.051	0.051

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	9295	9295	9295	9295	9295
Minimum	82.934	23.443	76.594	86.757	57.944
Maximum	724.570	713.287	725.409	726.341	718.975
Mean	385.482	385.246	385.013	385.203	385.323
Standard Dev	90.136	89.720	89.575	89.817	89.514
Skewness(G1)	0.322	0.326	0.328	0.316	0.342
SE Skewness	0.025	0.025	0.025	0.025	0.025
Kurtosis(G2)	0.031	0.029	0.075	-0.016	0.022
SE Kurtosis	0.051	0.051	0.051	0.051	0.051

Table C7 - Bulgaria

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4229	4280	4243	4261	4267
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.361	-0.022	0.445	0.056	0.332
Standard Dev	0.841	1.038	0.977	1.087	0.913
Skewness(G1)	-0.075	0.091	0.138	0.217	0.196
SE Skewness	0.038	0.037	0.038	0.038	0.037
Kurtosis(G2)	0.277	1.887	0.397	0.295	0.521
SE Kurtosis	0.075	0.075	0.075	0.075	0.075

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4246	4405	4410	4371	4357
Minimum	-1.259	-3.682	-5.268	-1.443	1.000
Maximum	3.027	2.482	3.419	1.068	6.000
Mean	0.537	-0.620	-0.557	0.263	3.143
Standard Dev	0.983	0.891	0.990	0.859	1.508
Skewness(G1)	0.177	-0.049	-0.221	-0.699	0.232
SE Skewness	0.038	0.037	0.037	0.037	0.037
Kurtosis(G2)	0.124	0.345	1.179	-0.669	-0.844
SE Kurtosis	0.075	0.074	0.074	0.074	0.074

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4498	4396	4206	4396	4289
Minimum	2.000	-3.777	16.000	-3.969	1.000
Maximum	3.000	0.507	90.000	2.716	3.000
Mean	2.955	-0.684	48.034	-0.154	1.003
Standard Dev	0.207	0.982	16.256	0.980	0.070
Skewness(G1)	-4.409	-0.327	0.481	0.016	25.129
SE Skewness	0.037	0.037	0.038	0.037	0.037

Kurtosis(G2)	17.446	-0.500	-0.644	-0.195	667.004
SE Kurtosis	0.073	0.074	0.075	0.074	0.075

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4498	4498	4498	4498	4498
Minimum	106.340	104.381	94.404	39.108	83.867
Maximum	801.965	790.682	752.917	765.505	783.222
Mean	439.435	439.466	438.668	438.459	439.237
Standard Dev	104.558	104.821	103.934	103.909	104.342
Skewness(G1)	0.086	0.064	0.048	0.069	0.072
SE Skewness	0.037	0.037	0.037	0.037	0.037
Kurtosis(G2)	-0.283	-0.324	-0.276	-0.255	-0.222
SE Kurtosis	0.073	0.073	0.073	0.073	0.073

Table C8 - Canada

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	18074	22143	17911	17968	17956
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.274	0.167	0.381	0.372	0.209
Standard Dev	1.094	1.085	1.013	0.874	0.994
Skewness(G1)	-0.199	-0.107	-0.044	-0.040	-0.181
SE Skewness	0.018	0.016	0.018	0.018	0.018
Kurtosis(G2)	-0.135	1.673	0.563	1.266	0.657
SE Kurtosis	0.036	0.033	0.037	0.037	0.037

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	17905	22177	22179	22089	21984
Minimum	-1.259	-4.397	-6.278	-1.833	1.000
Maximum	3.027	1.966	2.859	1.284	6.000
Mean	0.154	0.085	-0.058	-0.142	3.610
Standard Dev	1.017	0.683	0.811	1.102	1.374
Skewness(G1)	0.251	0.096	0.254	-0.143	-0.011
SE Skewness	0.018	0.016	0.016	0.016	0.017
Kurtosis(G2)	-0.335	1.395	1.919	-1.144	-0.681
SE Kurtosis	0.037	0.033	0.033	0.033	0.033

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	22646	22148	21776	22136	21743
Minimum	2.000	-4.126	16.000	-4.371	1.000
Maximum	3.000	0.719	90.000	2.755	3.000
Mean	2.836	-0.055	52.602	0.294	1.173
Standard Dev	0.370	0.877	15.750	0.812	0.500
Skewness(G1)	-1.820	-0.927	0.046	-0.207	2.868
SE Skewness	0.016	0.016	0.017	0.016	0.017
Kurtosis(G2)	1.312	0.490	-0.600	-0.023	7.028
SE Kurtosis	0.033	0.033	0.033	0.033	0.033

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	22646	22646	22646	22646	22646
Minimum	126.108	139.069	75.008	120.700	124.430
Maximum	834.975	850.547	846.630	831.897	852.412
Mean	522.504	522.748	522.419	522.425	522.521
Standard Dev	95.656	96.007	95.377	95.653	95.624
Skewness(G1)	-0.163	-0.157	-0.164	-0.170	-0.172
SE Skewness	0.016	0.016	0.016	0.016	0.016
Kurtosis(G2)	-0.195	-0.175	-0.180	-0.152	-0.163
SE Kurtosis	0.033	0.033	0.033	0.033	0.033

Table C9 - Chile

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT

N of cases	4870	5127	4970	4999	5006
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.180	0.076	0.424	0.262	0.260
Standard Dev	0.899	0.936	1.044	1.077	0.952
Skewness(G1)	0.008	0.034	0.004	0.026	0.008
SE Skewness	0.035	0.034	0.035	0.035	0.035
Kurtosis(G2)	0.038	1.342	0.124	0.190	0.483
SE Kurtosis	0.070	0.068	0.069	0.069	0.069

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4972	5135	5135	5128	5073
Minimum	-1.259	-3.893	-4.790	-1.412	1.000
Maximum	3.027	2.106	3.241	1.046	6.000
Mean	0.630	-0.999	-0.838	-0.060	2.540
Standard Dev	0.977	0.952	1.089	0.849	1.201
Skewness(G1)	0.064	0.157	0.084	-0.166	0.662
SE Skewness	0.035	0.034	0.034	0.034	0.034
Kurtosis(G2)	-0.033	0.044	0.106	-1.050	0.205
SE Kurtosis	0.069	0.068	0.068	0.068	0.069

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	5233	5134	5007	5128	5053
Minimum	2.000	-4.472	16.000	-4.497	1.000
Maximum	3.000	0.934	88.000	2.462	3.000
Mean	2.972	-0.633	41.265	-0.636	1.008
Standard Dev	0.166	1.082	16.755	1.173	0.122
Skewness(G1)	-5.672	-0.081	0.539	0.109	15.357
SE Skewness	0.034	0.034	0.035	0.034	0.034
Kurtosis(G2)	30.180	-0.482	-0.408	-0.595	240.257
SE Kurtosis	0.068	0.068	0.069	0.068	0.069

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	5233	5233	5233	5233	5233
Minimum	73.610	168.722	162.661	157.998	119.487
Maximum	726.808	775.856	743.312	775.856	737.717
Mean	442.553	443.018	443.077	443.319	443.595
Standard Dev	90.893	90.300	91.481	91.588	91.553
Skewness(G1)	0.116	0.181	0.136	0.119	0.152
SE Skewness	0.034	0.034	0.034	0.034	0.034
Kurtosis(G2)	-0.234	-0.243	-0.268	-0.216	-0.246
SE Kurtosis	0.068	0.068	0.068	0.068	0.068

Table C10 - Chinese - Taipei

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	8777	8803	8776	8800	8800
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	-0.399	0.228	0.130	-0.101	-0.061
Standard Dev	0.974	0.997	1.035	0.962	0.958
Skewness(G1)	0.179	-0.154	-0.092	-0.234	-0.099
SE Skewness	0.026	0.026	0.026	0.026	0.026
Kurtosis(G2)	0.282	2.045	0.824	0.771	0.922
SE Kurtosis	0.052	0.052	0.052	0.052	0.052

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	8776	8804	8806	8776	8793
Minimum	-1.259	-3.590	-5.652	-1.373	1.000
Maximum	3.027	2.643	3.522	1.004	6.000
Mean	0.090	-0.202	-0.335	0.148	3.199
Standard Dev	0.997	0.652	0.793	0.872	1.404
Skewness(G1)	0.303	0.033	-0.113	-0.534	0.296

SE Skewness	0.026	0.026	0.026	0.026	0.026
Kurtosis(G2)	-0.205	1.245	1.614	-1.043	-0.618
SE Kurtosis	0.052	0.052	0.052	0.052	0.052

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	8815	8800	8413	8794	8670
Minimum	2.000	-4.185	16.000	-4.158	1.000
Maximum	3.000	0.584	90.000	2.336	3.000
Mean	2.733	-0.444	49.550	-0.235	1.008
Standard Dev	0.442	0.864	15.913	0.797	0.109
Skewness(G1)	-1.054	-0.454	0.132	-0.002	15.137
SE Skewness	0.026	0.026	0.027	0.026	0.026
Kurtosis(G2)	-0.889	-0.149	-0.703	-0.115	246.265
SE Kurtosis	0.052	0.052	0.053	0.052	0.053

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	8815	8815	8815	8815	8815
Minimum	204.436	207.140	215.625	178.326	206.207
Maximum	808.399	809.425	810.264	817.910	797.303
Mean	543.894	543.827	543.882	543.361	543.592
Standard Dev	91.828	91.475	91.709	91.826	91.807
Skewness(G1)	-0.347	-0.339	-0.352	-0.362	-0.352
SE Skewness	0.026	0.026	0.026	0.026	0.026
Kurtosis(G2)	-0.224	-0.239	-0.243	-0.187	-0.244
SE Kurtosis	0.052	0.052	0.052	0.052	0.052

Table C11 - Columbia

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4299	4450	4357	4367	4387
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.751	0.099	0.590	0.295	0.383
Standard Dev	0.769	0.918	0.984	0.909	0.829
Skewness(G1)	-0.113	0.197	0.064	-0.148	0.331
SE Skewness	0.037	0.037	0.037	0.037	0.037
Kurtosis(G2)	0.111	1.125	0.129	0.818	0.629
SE Kurtosis	0.075	0.073	0.074	0.074	0.074

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4350	4458	4459	4339	4343
Minimum	-1.259	-4.721	-6.518	-1.439	1.000
Maximum	3.027	2.048	3.550	1.081	6.000
Mean	0.668	-1.670	-1.204	0.030	2.238
Standard Dev	0.939	1.054	1.226	0.866	1.145
Skewness(G1)	0.079	0.027	-0.078	-0.311	0.811
SE Skewness	0.037	0.037	0.037	0.037	0.037
Kurtosis(G2)	0.321	0.252	0.610	-0.982	0.367
SE Kurtosis	0.074	0.073	0.073	0.074	0.074

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4478	4423	4250	4453	4332
Minimum	2.000	-4.844	16.000	-5.027	1.000
Maximum	3.000	1.315	90.000	2.698	3.000
Mean	2.610	-0.843	43.045	-0.932	1.004
Standard Dev	0.488	1.267	17.364	1.242	0.073
Skewness(G1)	-0.452	0.154	0.428	0.032	20.821
SE Skewness	0.037	0.037	0.038	0.037	0.037
Kurtosis(G2)	-1.797	-0.288	-0.619	-0.653	479.014
SE Kurtosis	0.073	0.074	0.075	0.073	0.074

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4478	4478	4478	4478	4478

Minimum	87.131	81.536	84.333	44.890	84.053
Maximum	686.338	709.557	686.338	706.293	683.354
Mean	391.526	392.197	391.765	392.156	391.641
Standard Dev	85.136	85.108	84.927	85.693	84.895
Skewness(G1)	-0.060	-0.012	-0.055	-0.117	-0.022
SE Skewness	0.037	0.037	0.037	0.037	0.037
Kurtosis(G2)	0.001	0.034	0.014	0.167	-0.019
SE Kurtosis	0.073	0.073	0.073	0.073	0.073

Table C12 - Croatia

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4545	5194	4529	4547	4553
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	-0.027	0.140	0.107	-0.352	0.280
Standard Dev	0.864	0.898	1.024	1.039	0.965
Skewness(G1)	0.014	-0.165	-0.056	0.147	-0.037
SE Skewness	0.036	0.034	0.036	0.036	0.036
Kurtosis(G2)	0.646	1.857	0.588	-0.034	0.704
SE Kurtosis	0.073	0.068	0.073	0.073	0.073

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4529	5207	5207	5048	5175
Minimum	-1.259	-3.817	-3.739	-1.439	1.000
Maximum	3.027	2.368	3.516	1.086	6.000
Mean	0.239	-0.427	-0.274	-0.215	2.504
Standard Dev	0.966	0.787	0.892	0.938	1.243
Skewness(G1)	0.247	0.140	0.064	0.073	0.632
SE Skewness	0.036	0.034	0.034	0.034	0.034
Kurtosis(G2)	-0.155	0.251	0.332	-1.294	-0.059
SE Kurtosis	0.073	0.068	0.068	0.069	0.068

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	5213	5185	5025	5205	5135
Minimum	2.000	-4.094	16.000	-3.109	1.000
Maximum	3.000	0.979	90.000	2.567	3.000
Mean	2.999	-0.008	46.646	-0.110	1.195
Standard Dev	0.028	0.914	15.089	0.870	0.550
Skewness(G1)	-36.069	-0.339	0.637	0.231	2.692
SE Skewness	0.034	0.034	0.035	0.034	0.034
Kurtosis(G2)	1299.498	-0.878	-0.006	-0.110	5.700
SE Kurtosis	0.068	0.068	0.069	0.068	0.068

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	5213	5213	5213	5213	5213
Minimum	151.844	176.648	197.535	144.944	165.458
Maximum	804.203	802.991	793.666	804.856	771.287
Mean	493.305	493.496	494.189	493.576	493.692
Standard Dev	85.102	85.266	85.132	85.635	85.111
Skewness(G1)	-0.006	0.004	0.007	0.003	0.040
SE Skewness	0.034	0.034	0.034	0.034	0.034
Kurtosis(G2)	-0.137	-0.085	-0.202	-0.071	-0.165
SE Kurtosis	0.068	0.068	0.068	0.068	0.068

Table C13 - Czech Republic

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	5748	5794	5723	5733	5736
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	-0.019	0.232	-0.112	-0.266	0.111
Standard Dev	0.805	0.888	0.916	0.897	0.936

Skewness(G1)	0.025	0.163	0.006	-0.236	-0.114
SE Skewness	0.032	0.032	0.032	0.032	0.032
Kurtosis(G2)	1.021	1.968	0.917	0.385	0.818
SE Kurtosis	0.065	0.064	0.065	0.065	0.065

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	5728	5918	5921	5891	5877
Minimum	-1.259	-3.719	-5.884	-1.527	1.000
Maximum	3.027	2.080	3.338	1.116	6.000
Mean	-0.267	-0.390	0.035	0.076	3.812
Standard Dev	0.914	0.763	0.865	0.924	1.303
Skewness(G1)	0.604	0.084	-0.073	-0.393	-0.073
SE Skewness	0.032	0.032	0.032	0.032	0.032
Kurtosis(G2)	-0.097	0.394	1.573	-1.003	-0.587
SE Kurtosis	0.065	0.064	0.064	0.064	0.064

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	5932	5907	5773	5903	5885
Minimum	2.000	-4.058	16.000	-3.890	1.000
Maximum	3.000	0.997	90.000	2.413	3.000
Mean	2.489	0.290	50.764	0.168	1.029
Standard Dev	0.500	0.897	14.698	0.788	0.226
Skewness(G1)	0.046	-0.931	0.348	0.005	8.013
SE Skewness	0.032	0.032	0.032	0.032	0.032
Kurtosis(G2)	-1.999	0.079	-0.212	-0.214	64.554
SE Kurtosis	0.064	0.064	0.064	0.064	0.064

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	5932	5932	5932	5932	5932
Minimum	133.474	171.053	195.111	152.217	178.233
Maximum	820.521	855.116	897.917	875.537	846.724
Mean	537.717	537.488	537.556	537.628	537.670
Standard Dev	102.846	103.156	102.140	102.919	102.269
Skewness(G1)	-0.152	-0.120	-0.136	-0.151	-0.143
SE Skewness	0.032	0.032	0.032	0.032	0.032
Kurtosis(G2)	-0.413	-0.453	-0.433	-0.375	-0.451
SE Kurtosis	0.064	0.064	0.064	0.064	0.064

Table C14 - Denmark

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4243	4482	4229	4246	4246
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	-0.092	-0.088	0.184	0.664	-0.006
Standard Dev	0.996	1.020	0.801	0.768	0.923
Skewness(G1)	-0.060	-0.016	0.094	-0.080	-0.154
SE Skewness	0.038	0.037	0.038	0.038	0.038
Kurtosis(G2)	0.224	1.033	1.105	1.421	0.737
SE Kurtosis	0.075	0.073	0.075	0.075	0.075

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4228	4507	4507	4477	4420
Minimum	-1.259	-2.287	-2.866	-1.755	1.000
Maximum	3.027	3.267	3.513	1.314	6.000
Mean	-0.105	0.892	0.384	-0.095	3.393
Standard Dev	0.908	0.945	0.927	1.082	1.412
Skewness(G1)	0.306	0.281	0.253	-0.105	0.079
SE Skewness	0.038	0.036	0.036	0.037	0.037
Kurtosis(G2)	-0.325	0.203	0.524	-1.160	-0.724
SE Kurtosis	0.075	0.073	0.073	0.073	0.074

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG

N of cases	4532	4506	4276	4496	4493
Minimum	2.000	-4.107	16.000	-3.426	1.000
Maximum	3.000	0.917	90.000	2.963	3.000
Mean	2.007	0.127	49.254	0.303	1.113
Standard Dev	0.081	0.842	17.098	0.892	0.413
Skewness(G1)	12.173	-0.672	0.188	-0.181	3.768
SE Skewness	0.036	0.036	0.037	0.037	0.037
Kurtosis(G2)	146.236	-0.181	-0.870	-0.005	13.318
SE Kurtosis	0.073	0.073	0.075	0.073	0.073

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4532	4532	4532	4532	4532
Minimum	132.449	137.018	139.815	145.876	97.854
Maximum	783.688	802.338	793.946	811.663	829.846
Mean	495.121	495.010	494.783	494.108	494.556
Standard Dev	92.459	92.492	93.236	92.621	92.959
Skewness(G1)	-0.068	-0.108	-0.101	-0.120	-0.119
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.125	-0.139	-0.164	-0.196	-0.168
SE Kurtosis	0.073	0.073	0.073	0.073	0.073

Table C15 - Estonia

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4819	4849	4821	4828	4830
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.113	0.038	0.201	-0.106	0.232
Standard Dev	0.805	0.857	0.801	0.814	0.766
Skewness(G1)	0.181	0.316	0.158	-0.092	0.038
SE Skewness	0.035	0.035	0.035	0.035	0.035
Kurtosis(G2)	0.652	1.154	0.926	0.981	1.289
SE Kurtosis	0.071	0.070	0.071	0.070	0.070

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4821	4856	4856	4844	4840
Minimum	-1.259	-3.528	-3.764	-1.433	1.000
Maximum	3.027	2.310	3.483	1.072	6.000
Mean	0.151	-0.376	0.007	0.365	3.839
Standard Dev	0.864	0.806	0.866	0.805	1.319
Skewness(G1)	0.087	0.103	0.270	-0.844	-0.084
SE Skewness	0.035	0.035	0.035	0.035	0.035
Kurtosis(G2)	-0.066	0.207	0.646	-0.312	-0.670
SE Kurtosis	0.071	0.070	0.070	0.070	0.070

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4865	4852	4785	4853	4756
Minimum	2.000	-3.875	16.000	-3.890	1.000
Maximum	3.000	0.594	90.000	2.817	3.000
Mean	2.020	-0.112	50.806	0.180	1.131
Standard Dev	0.138	0.781	16.555	0.798	0.368
Skewness(G1)	6.947	-0.646	0.136	0.015	2.813
SE Skewness	0.035	0.035	0.035	0.035	0.036
Kurtosis(G2)	46.279	-0.496	-1.015	-0.547	7.587
SE Kurtosis	0.070	0.070	0.071	0.070	0.071

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4865	4865	4865	4865	4865
Minimum	230.265	208.818	245.278	208.818	234.275
Maximum	792.547	799.168	798.328	810.730	824.717
Mean	534.500	533.623	533.739	533.369	533.396
Standard Dev	83.534	83.545	83.932	83.436	82.892
Skewness(G1)	-0.083	-0.096	-0.064	-0.088	-0.098

SE Skewness	0.035	0.035	0.035	0.035	0.035
Kurtosis(G2)	-0.169	-0.092	-0.216	-0.158	-0.145
SE Kurtosis	0.070	0.070	0.070	0.070	0.070

Table C16 - Finland

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4650	4695	4670	4673	4675
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.065	0.026	-0.135	0.020	-0.135
Standard Dev	0.846	0.922	0.786	0.766	0.761
Skewness(G1)	0.034	0.057	-0.208	-0.249	-0.370
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	0.604	1.990	1.041	1.043	1.307
SE Kurtosis	0.072	0.071	0.072	0.072	0.072

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4671	4708	4708	4694	4683
Minimum	-1.259	-2.457	-2.862	-1.615	1.000
Maximum	3.027	2.439	3.114	1.175	6.000
Mean	-0.268	0.400	0.148	0.156	3.631
Standard Dev	0.783	0.733	0.792	0.995	1.254
Skewness(G1)	0.345	-0.112	0.083	-0.480	-0.001
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.142	0.469	0.632	-1.032	-0.477
SE Kurtosis	0.072	0.071	0.071	0.071	0.072

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4714	4702	4587	4697	4673
Minimum	2.000	-3.922	16.000	-2.512	1.000
Maximum	3.000	1.207	90.000	3.113	3.000
Mean	2.000	-0.053	48.874	0.263	1.028
Standard Dev	0.015	1.011	16.975	0.787	0.232
Skewness(G1)	68.659	-0.077	0.191	-0.163	8.200
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	4714.000	-0.951	-0.857	-0.193	66.041
SE Kurtosis	0.071	0.071	0.072	0.071	0.072

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4714	4714	4714	4714	4714
Minimum	210.031	235.207	173.664	183.921	176.461
Maximum	851.479	837.492	831.618	851.759	836.653
Mean	563.748	563.852	563.162	563.579	562.553
Standard Dev	85.859	85.218	85.879	85.711	85.202
Skewness(G1)	-0.148	-0.152	-0.189	-0.153	-0.150
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	0.042	-0.069	-0.033	0.115	0.061
SE Kurtosis	0.071	0.071	0.071	0.071	0.071

Table C17 - France

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4488	4633	4531	4546	4554
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	-0.107	-0.050	0.001	0.289	-0.165
Standard Dev	0.995	0.935	0.956	0.843	0.907
Skewness(G1)	-0.016	-0.187	-0.027	-0.432	-0.097
SE Skewness	0.037	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.018	1.941	0.489	0.954	0.598
SE Kurtosis	0.073	0.072	0.073	0.073	0.073

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4530	4648	4648	4627	4598
Minimum	-1.259	-4.080	-3.912	-1.534	1.000
Maximum	3.027	2.131	3.365	1.127	6.000
Mean	-0.001	-0.234	0.001	-0.166	3.298
Standard Dev	0.939	0.711	0.825	0.976	1.427
Skewness(G1)	0.281	0.004	0.061	-0.077	0.171
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.379	1.265	0.949	-1.258	-0.746
SE Kurtosis	0.073	0.072	0.072	0.072	0.072

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4716	4645	4431	4606	4575
Minimum	2.000	-4.369	16.000	-3.318	1.000
Maximum	3.000	1.653	90.000	2.637	3.000
Mean	2.597	0.406	48.777	-0.083	1.161
Standard Dev	0.490	1.128	16.602	0.862	0.449
Skewness(G1)	-0.397	-0.325	0.257	-0.189	2.855
SE Skewness	0.036	0.036	0.037	0.036	0.036
Kurtosis(G2)	-1.843	-0.772	-0.546	0.042	7.497
SE Kurtosis	0.071	0.072	0.074	0.072	0.072

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4716	4716	4716	4716	4716
Minimum	170.773	169.841	105.500	98.040	146.529
Maximum	801.126	791.521	822.573	775.016	851.200
Mean	496.103	495.890	496.290	496.350	495.980
Standard Dev	101.490	101.238	100.812	101.660	100.777
Skewness(G1)	-0.222	-0.213	-0.226	-0.247	-0.224
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.379	-0.314	-0.280	-0.299	-0.306
SE Kurtosis	0.071	0.071	0.071	0.071	0.071

Table C18 - Germany

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4540	4577	4539	4547	4555
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.256	0.072	-0.084	0.164	0.100
Standard Dev	0.992	0.976	0.893	0.855	0.922
Skewness(G1)	-0.020	-0.291	-0.133	-0.281	-0.070
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.085	2.549	0.694	0.975	0.680
SE Kurtosis	0.073	0.072	0.073	0.073	0.073

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4545	4729	4730	4638	4646
Minimum	-1.259	-2.842	-3.048	-1.479	1.000
Maximum	3.027	2.282	3.251	1.143	6.000
Mean	-0.073	0.241	0.336	0.086	3.507
Standard Dev	0.956	0.780	0.891	0.924	1.419
Skewness(G1)	0.350	0.223	0.279	-0.320	0.071
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.461	0.328	0.656	-1.089	-0.716
SE Kurtosis	0.073	0.071	0.071	0.072	0.072

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4891	4718	4498	4686	4603
Minimum	2.000	-4.009	16.000	-3.532	1.000
Maximum	3.000	1.173	90.000	2.993	3.000
Mean	2.020	0.368	49.191	0.303	1.208
Standard Dev	0.140	0.950	16.350	0.931	0.544

Skewness(G1)	6.853	-0.713	0.270	-0.076	2.531
SE Skewness	0.035	0.036	0.037	0.036	0.036
Kurtosis(G2)	44.976	-0.578	-0.566	0.133	5.079
SE Kurtosis	0.070	0.071	0.073	0.072	0.072

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4891	4891	4891	4891	4891
Minimum	185.786	150.352	159.584	190.169	191.381
Maximum	826.396	823.598	788.817	815.952	822.479
Mean	515.953	516.108	516.043	516.703	516.226
Standard Dev	100.018	100.161	99.926	99.607	99.757
Skewness(G1)	-0.201	-0.181	-0.182	-0.171	-0.171
SE Skewness	0.035	0.035	0.035	0.035	0.035
Kurtosis(G2)	-0.300	-0.260	-0.319	-0.278	-0.283
SE Kurtosis	0.070	0.070	0.070	0.070	0.070

Table C19 - Greece

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4815	4854	4833	4837	4838
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.036	-0.118	0.331	-0.058	0.562
Standard Dev	0.995	0.948	0.972	1.081	0.951
Skewness(G1)	-0.052	0.260	-0.093	-0.093	-0.133
SE Skewness	0.035	0.035	0.035	0.035	0.035
Kurtosis(G2)	0.067	1.606	0.629	-0.145	0.413
SE Kurtosis	0.071	0.070	0.070	0.070	0.070

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4834	4866	4867	4815	4835
Minimum	-1.259	-3.791	-4.024	-1.653	1.000
Maximum	3.027	2.525	3.309	1.218	6.000
Mean	0.349	-0.264	-0.408	0.054	3.274
Standard Dev	1.058	0.802	0.841	0.942	1.339
Skewness(G1)	0.093	0.179	0.348	-0.361	0.347
SE Skewness	0.035	0.035	0.035	0.035	0.035
Kurtosis(G2)	-0.487	0.264	0.889	-0.819	-0.493
SE Kurtosis	0.070	0.070	0.070	0.071	0.070

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4873	4863	4737	4862	4795
Minimum	2.000	-4.219	16.000	-2.839	1.000
Maximum	3.000	0.750	90.000	2.856	3.000
Mean	2.954	-0.595	48.918	-0.113	1.117
Standard Dev	0.210	0.863	16.820	0.974	0.457
Skewness(G1)	-4.315	0.001	0.307	0.020	3.759
SE Skewness	0.035	0.035	0.036	0.035	0.035
Kurtosis(G2)	16.629	-0.189	-0.526	-0.604	12.395
SE Kurtosis	0.070	0.070	0.071	0.070	0.071

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4873	4873	4873	4873	4873
Minimum	76.594	103.915	122.285	71.931	110.163
Maximum	735.666	763.640	773.245	740.608	791.894
Mean	476.761	476.634	476.516	475.463	477.833
Standard Dev	91.911	90.938	90.998	91.269	91.316
Skewness(G1)	-0.240	-0.190	-0.221	-0.239	-0.193
SE Skewness	0.035	0.035	0.035	0.035	0.035
Kurtosis(G2)	0.007	0.101	0.019	0.056	0.062
SE Kurtosis	0.070	0.070	0.070	0.070	0.070

Table C20 - Hong Kong - China

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	3713	4629	3721	3728	3728
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	-0.258	0.070	0.001	0.292	-0.288
Standard Dev	0.955	0.946	0.945	0.857	0.836
Skewness(G1)	-0.082	-0.163	-0.315	-0.428	-0.322
SE Skewness	0.040	0.036	0.040	0.040	0.040
Kurtosis(G2)	0.191	2.510	1.061	1.618	1.376
SE Kurtosis	0.080	0.072	0.080	0.080	0.080

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	3721	4629	4629	4628	4623
Minimum	-1.259	-4.476	-4.822	-1.467	1.000
Maximum	3.027	2.642	3.780	1.110	6.000
Mean	0.218	-0.422	-0.394	-0.302	2.581
Standard Dev	0.850	0.783	0.923	0.889	1.243
Skewness(G1)	0.038	-0.138	-0.003	0.133	0.520
SE Skewness	0.040	0.036	0.036	0.036	0.036
Kurtosis(G2)	0.143	0.519	0.408	-1.063	-0.174
SE Kurtosis	0.080	0.072	0.072	0.072	0.072

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4645	4628	4455	4614	4584
Minimum	2.000	-4.354	16.000	-3.280	1.000
Maximum	3.000	0.818	88.000	2.287	3.000
Mean	2.642	-0.011	42.768	-0.676	1.627
Standard Dev	0.479	0.835	13.571	0.928	0.783
Skewness(G1)	-0.593	-0.674	0.499	0.200	0.762
SE Skewness	0.036	0.036	0.037	0.036	0.036
Kurtosis(G2)	-1.648	-0.103	0.239	-0.207	-0.962
SE Kurtosis	0.072	0.072	0.073	0.072	0.072

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4645	4645	4645	4645	4645
Minimum	126.294	183.175	201.359	189.236	187.651
Maximum	812.315	793.386	833.576	817.724	812.129
Mean	546.094	545.646	546.160	546.281	546.264
Standard Dev	90.774	90.363	91.060	90.475	90.343
Skewness(G1)	-0.349	-0.347	-0.321	-0.304	-0.346
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.038	-0.044	-0.058	-0.094	-0.057
SE Kurtosis	0.072	0.072	0.072	0.072	0.072

Table C21 - Hungary

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4427	4469	4438	4441	4442
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	-0.218	-0.044	-0.003	-0.795	0.177
Standard Dev	0.893	0.848	0.960	0.960	0.894
Skewness(G1)	0.123	0.150	-0.213	0.425	-0.270
SE Skewness	0.037	0.037	0.037	0.037	0.037
Kurtosis(G2)	0.371	2.092	0.721	0.087	1.179
SE Kurtosis	0.074	0.073	0.073	0.073	0.073

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4437	4475	4475	4454	4464
Minimum	-1.259	-3.129	-3.643	-1.610	1.000
Maximum	3.027	2.255	3.442	1.327	6.000
Mean	-0.288	-0.334	-0.003	0.364	3.871

Standard Dev	0.931	0.837	0.965	0.980	1.410
Skewness(G1)	0.624	0.034	0.032	-0.659	-0.096
SE Skewness	0.037	0.037	0.037	0.037	0.037
Kurtosis(G2)	-0.241	0.006	0.148	-0.616	-0.812
SE Kurtosis	0.074	0.073	0.073	0.073	0.073

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4490	4471	4203	4474	4455
Minimum	2.000	-3.957	16.000	-3.035	1.000
Maximum	3.000	1.160	90.000	2.790	3.000
Mean	2.959	0.023	48.197	-0.053	1.030
Standard Dev	0.198	1.034	15.160	0.917	0.234
Skewness(G1)	-4.632	-0.262	0.368	0.113	8.022
SE Skewness	0.037	0.037	0.038	0.037	0.037
Kurtosis(G2)	19.468	-1.015	-0.307	-0.333	63.503
SE Kurtosis	0.073	0.073	0.076	0.073	0.073

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4490	4490	4490	4490	4490
Minimum	201.545	188.211	181.124	181.124	195.111
Maximum	770.634	766.345	753.383	785.274	764.759
Mean	508.945	508.244	508.670	509.275	508.468
Standard Dev	86.912	86.576	86.788	87.488	86.110
Skewness(G1)	-0.083	-0.097	-0.123	-0.116	-0.116
SE Skewness	0.037	0.037	0.037	0.037	0.037
Kurtosis(G2)	-0.112	-0.174	-0.178	-0.140	-0.163
SE Kurtosis	0.073	0.073	0.073	0.073	0.073

Table C22 - Iceland

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	3559	3747	3548	3549	3551
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.104	0.136	-0.014	-0.625	-0.187
Standard Dev	1.102	1.161	0.993	0.974	0.872
Skewness(G1)	-0.178	-0.403	-0.111	0.163	-0.574
SE Skewness	0.041	0.040	0.041	0.041	0.041
Kurtosis(G2)	-0.137	1.611	0.465	-0.225	0.665
SE Kurtosis	0.082	0.080	0.082	0.082	0.082

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	3547	3752	3752	3751	3730
Minimum	-1.259	-3.000	-3.671	-1.620	1.000
Maximum	3.027	3.207	3.918	1.213	6.000
Mean	-0.429	0.986	0.922	0.732	3.952
Standard Dev	0.873	0.779	0.869	0.769	1.276
Skewness(G1)	0.741	0.171	0.336	-1.448	-0.128
SE Skewness	0.041	0.040	0.040	0.040	0.040
Kurtosis(G2)	-0.147	0.554	0.804	1.139	-0.621
SE Kurtosis	0.082	0.080	0.080	0.080	0.080

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	3789	3751	3696	3745	3699
Minimum	2.000	-3.999	16.000	-3.203	1.000
Maximum	3.000	0.855	90.000	3.311	3.000
Mean	2.005	0.274	54.011	0.774	1.032
Standard Dev	0.072	0.780	16.992	0.876	0.241
Skewness(G1)	13.660	-1.026	-0.028	-0.248	7.751
SE Skewness	0.040	0.040	0.040	0.040	0.040
Kurtosis(G2)	184.701	0.296	-0.887	-0.130	59.228
SE Kurtosis	0.080	0.080	0.081	0.080	0.080

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	3789	3789	3789	3789	3789
Minimum	156.600	131.889	156.600	140.934	157.066
Maximum	813.528	821.454	753.849	815.206	785.553
Mean	490.800	491.109	490.170	491.497	491.186
Standard Dev	96.543	96.576	96.466	96.995	96.593
Skewness(G1)	-0.147	-0.125	-0.185	-0.166	-0.133
SE Skewness	0.040	0.040	0.040	0.040	0.040
Kurtosis(G2)	-0.197	-0.189	-0.190	-0.142	-0.206
SE Kurtosis	0.080	0.080	0.080	0.080	0.080

Table C23 - Indonesia

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	10272	10582	10350	10377	10389
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.227	-0.701	0.159	0.414	0.553
Standard Dev	0.754	0.828	0.997	0.896	0.964
Skewness(G1)	0.211	0.065	0.101	0.064	0.115
SE Skewness	0.024	0.024	0.024	0.024	0.024
Kurtosis(G2)	0.189	1.885	0.710	1.034	0.256
SE Kurtosis	0.048	0.048	0.048	0.048	0.048

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	10355	10640	10646	10450	10241
Minimum	-1.259	-4.997	-6.173	-1.544	1.000
Maximum	3.027	2.127	3.317	1.134	6.000
Mean	0.799	-2.614	-1.938	-0.593	2.337
Standard Dev	0.965	1.257	1.106	0.863	1.055
Skewness(G1)	0.017	0.124	-0.088	0.460	0.952
SE Skewness	0.024	0.024	0.024	0.024	0.024
Kurtosis(G2)	0.245	-0.368	0.413	-0.749	1.380
SE Kurtosis	0.048	0.047	0.047	0.048	0.048

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	10647	10629	9751	10633	10466
Minimum	2.000	-4.345	16.000	-4.647	1.000
Maximum	3.000	1.079	90.000	1.723	3.000
Mean	2.412	-1.382	37.956	-1.455	1.006
Standard Dev	0.492	1.016	15.658	1.055	0.104
Skewness(G1)	0.356	0.221	0.712	0.234	18.581
SE Skewness	0.024	0.024	0.025	0.024	0.024
Kurtosis(G2)	-1.874	0.391	-0.301	-0.543	347.931
SE Kurtosis	0.047	0.048	0.050	0.047	0.048

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	10647	10647	10647	10647	10647
Minimum	160.423	128.719	162.195	169.655	161.449
Maximum	670.859	660.602	625.168	656.872	707.226
Mean	384.774	384.709	384.653	384.779	384.895
Standard Dev	63.464	63.397	63.851	63.472	63.891
Skewness(G1)	0.253	0.269	0.258	0.277	0.266
SE Skewness	0.024	0.024	0.024	0.024	0.024
Kurtosis(G2)	0.138	0.173	0.100	0.148	0.203
SE Kurtosis	0.047	0.047	0.047	0.047	0.047

Table C24 - Ireland

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	3938	4500	3912	3925	3928
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474

Mean	-0.127	0.021	0.045	0.373	-0.378
Standard Dev	1.040	1.033	1.026	0.809	1.039
Skewness(G1)	-0.027	-0.231	0.017	-0.287	-0.145
SE Skewness	0.039	0.037	0.039	0.039	0.039
Kurtosis(G2)	0.049	1.585	0.285	1.429	0.099
SE Kurtosis	0.078	0.073	0.078	0.078	0.078

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	3911	4513	4513	4473	4477
Minimum	-1.259	-3.199	-5.657	-1.509	1.000
Maximum	3.027	2.323	3.175	1.141	6.000
Mean	-0.265	0.109	-0.026	-0.180	3.419
Standard Dev	0.937	0.709	0.846	0.954	1.413
Skewness(G1)	0.630	0.148	0.251	0.035	0.084
SE Skewness	0.039	0.036	0.036	0.037	0.037
Kurtosis(G2)	-0.090	0.169	0.893	-1.207	-0.756
SE Kurtosis	0.078	0.073	0.073	0.073	0.073

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4585	4506	4397	4501	4442
Minimum	2.000	-4.171	16.000	-3.543	1.000
Maximum	3.000	0.670	90.000	2.564	3.000
Mean	2.380	-0.097	49.217	-0.003	1.098
Standard Dev	0.485	0.850	16.373	0.855	0.419
Skewness(G1)	0.494	-0.797	0.250	0.017	4.170
SE Skewness	0.036	0.036	0.037	0.036	0.037
Kurtosis(G2)	-1.757	0.049	-0.625	-0.203	15.727
SE Kurtosis	0.072	0.073	0.074	0.073	0.073

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4585	4585	4585	4585	4585
Minimum	126.854	182.243	165.085	195.298	185.973
Maximum	777.627	802.058	844.019	812.595	821.640
Mean	509.353	509.766	508.880	508.847	510.588
Standard Dev	94.652	94.123	93.906	93.368	93.744
Skewness(G1)	-0.129	-0.131	-0.083	-0.126	-0.119
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.181	-0.187	-0.186	-0.252	-0.229
SE Kurtosis	0.072	0.072	0.072	0.072	0.072

Table C25 - Israel

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4066	4276	3904	3964	3988
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.271	0.031	0.047	0.293	0.293
Standard Dev	1.130	1.141	1.128	1.145	1.011
Skewness(G1)	-0.351	-0.141	-0.241	-0.222	-0.285
SE Skewness	0.038	0.037	0.039	0.039	0.039
Kurtosis(G2)	-0.120	2.138	0.292	0.208	1.086
SE Kurtosis	0.077	0.075	0.078	0.078	0.078

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	3904	4399	4401	4340	4227
Minimum	-1.259	-3.504	-5.208	-1.403	1.000
Maximum	3.027	2.560	3.504	1.032	6.000
Mean	0.416	-0.122	0.054	0.104	3.542
Standard Dev	1.117	0.954	1.019	0.896	1.456
Skewness(G1)	0.070	-0.012	0.168	-0.435	0.126
SE Skewness	0.039	0.037	0.037	0.037	0.038
Kurtosis(G2)	-0.622	0.205	0.571	-1.145	-0.791
SE Kurtosis	0.078	0.074	0.074	0.074	0.075

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4584	4386	3852	4344	4201
Minimum	2.000	-3.707	16.000	-3.842	1.000
Maximum	3.000	0.177	90.000	2.692	3.000
Mean	2.877	-0.219	53.269	0.229	1.346
Standard Dev	0.328	0.639	15.992	0.856	0.679
Skewness(G1)	-2.302	-1.572	-0.170	-0.599	1.694
SE Skewness	0.036	0.037	0.039	0.037	0.038
Kurtosis(G2)	3.301	2.103	-0.456	0.765	1.283
SE Kurtosis	0.072	0.074	0.079	0.074	0.076

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4584	4584	4584	4584	4584
Minimum	107.645	89.648	100.651	94.124	127.227
Maximum	833.762	849.428	852.505	852.412	814.180
Mean	455.434	455.660	456.150	455.552	455.363
Standard Dev	110.898	111.830	112.044	111.384	112.365
Skewness(G1)	0.022	0.029	0.001	0.023	0.025
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.339	-0.351	-0.373	-0.354	-0.365
SE Kurtosis	0.072	0.072	0.072	0.072	0.072

Table C26 - Italy

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	19614	21630	19712	19747	19770
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.120	-0.205	-0.150	-0.405	0.321
Standard Dev	0.892	0.793	0.982	1.130	0.976
Skewness(G1)	-0.036	0.031	0.043	0.092	-0.169
SE Skewness	0.017	0.017	0.017	0.017	0.017
Kurtosis(G2)	0.325	3.263	0.392	-0.448	0.642
SE Kurtosis	0.035	0.033	0.035	0.035	0.035

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	19715	21690	21697	21633	21525
Minimum	-1.259	-4.038	-6.087	-1.383	1.000
Maximum	3.027	2.328	3.529	1.014	6.000
Mean	-0.086	-0.162	0.129	0.205	3.393
Standard Dev	1.019	0.714	0.855	0.814	1.356
Skewness(G1)	0.542	0.191	0.180	-0.562	0.191
SE Skewness	0.017	0.017	0.017	0.017	0.017
Kurtosis(G2)	-0.287	0.590	1.130	-0.827	-0.600
SE Kurtosis	0.035	0.033	0.033	0.033	0.033

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	21773	21677	21344	21683	21260
Minimum	2.000	-4.290	16.000	-3.389	1.000
Maximum	3.000	1.206	90.000	3.022	3.000
Mean	2.992	0.239	46.378	-0.078	1.076
Standard Dev	0.090	0.980	16.322	0.957	0.374
Skewness(G1)	-10.988	-0.488	0.569	0.213	4.827
SE Skewness	0.017	0.017	0.017	0.017	0.017
Kurtosis(G2)	118.746	-0.602	-0.058	-0.328	21.625
SE Kurtosis	0.033	0.033	0.034	0.033	0.034

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	21773	21773	21773	21773	21773
Minimum	79.484	98.040	89.648	97.108	61.767
Maximum	808.399	807.653	808.399	804.762	800.473
Mean	487.157	487.497	487.298	487.048	486.765

Standard Dev	96.054	96.069	96.001	96.337	95.822
Skewness(G1)	-0.108	-0.109	-0.121	-0.107	-0.114
SE Skewness	0.017	0.017	0.017	0.017	0.017
Kurtosis(G2)	-0.265	-0.237	-0.233	-0.264	-0.256
SE Kurtosis	0.033	0.033	0.033	0.033	0.033

Table C27 - Japan

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	5890	5947	5897	5902	5904
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	-0.872	-0.529	-0.931	-0.519	-1.140
Standard Dev	0.983	0.979	1.056	1.071	0.908
Skewness(G1)	0.435	-0.546	0.231	0.015	0.176
SE Skewness	0.032	0.032	0.032	0.032	0.032
Kurtosis(G2)	0.364	3.045	-0.218	-0.492	-0.025
SE Kurtosis	0.064	0.064	0.064	0.064	0.064

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	5894	5950	5951	5919	5931
Minimum	-1.259	-3.816	-6.128	-1.448	1.000
Maximum	3.027	2.004	3.021	1.073	6.000
Mean	-0.241	-0.106	-0.482	-0.476	3.476
Standard Dev	0.888	0.657	0.762	0.891	1.389
Skewness(G1)	0.446	-0.063	0.056	0.392	0.047
SE Skewness	0.032	0.032	0.032	0.032	0.032
Kurtosis(G2)	-0.358	0.660	1.287	-1.049	-0.709
SE Kurtosis	0.064	0.063	0.063	0.064	0.064

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	5952	5947	5453	5862	5943
Minimum	3.000	-4.592	16.000	-2.656	1.000
Maximum	3.000	1.545	80.000	2.425	3.000
Mean	3.000	-0.577	50.352	-0.002	1.005
Standard Dev	0.000	1.045	14.700	0.693	0.099
Skewness(G1)	.	0.284	0.570	0.047	19.125
SE Skewness	.	0.032	0.033	0.032	0.032
Kurtosis(G2)	.	0.164	-0.567	-0.460	373.441
SE Kurtosis	.	0.064	0.066	0.064	0.064

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	5952	5952	5952	5952	5952
Minimum	82.934	93.285	116.970	21.391	80.137
Maximum	830.965	825.650	826.302	807.653	826.302
Mean	534.108	533.567	533.849	533.203	533.866
Standard Dev	98.731	99.642	99.496	100.399	99.645
Skewness(G1)	-0.343	-0.301	-0.311	-0.326	-0.351
SE Skewness	0.032	0.032	0.032	0.032	0.032
Kurtosis(G2)	0.045	0.015	0.031	0.100	0.103
SE Kurtosis	0.063	0.063	0.063	0.063	0.063

Table C28 - Jordan

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	6389	6466	6443	6445	6451
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.720	0.224	0.637	0.525	0.754
Standard Dev	0.845	0.975	1.008	0.986	0.949
Skewness(G1)	-0.445	0.093	-0.133	-0.190	-0.210
SE Skewness	0.031	0.030	0.031	0.031	0.030
Kurtosis(G2)	0.408	1.393	0.279	0.686	0.480

SE Kurtosis	0.061	0.061	0.061	0.061	0.061

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	6445	6499	6500	6288	6232
Minimum	-1.259	-3.811	-5.467	-1.395	1.000
Maximum	3.027	1.979	2.940	1.028	6.000
Mean	1.018	-1.346	-1.313	-0.323	2.473
Standard Dev	0.963	0.970	1.069	0.829	1.342
Skewness(G1)	-0.191	-0.119	-0.518	0.166	0.864
SE Skewness	0.031	0.030	0.030	0.031	0.031
Kurtosis(G2)	0.135	0.221	1.232	-1.047	0.281
SE Kurtosis	0.061	0.061	0.061	0.062	0.062

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	6509	6454	5302	6489	6268
Minimum	2.000	-3.856	16.000	-5.048	1.000
Maximum	2.000	0.377	90.000	2.209	3.000
Mean	2.000	-1.005	51.713	-0.492	1.270
Standard Dev	0.000	1.015	17.194	1.066	0.589
Skewness(G1)	.	-0.406	-0.025	-0.490	2.047
SE Skewness	.	0.030	0.034	0.030	0.031
Kurtosis(G2)	.	-0.170	-1.000	0.011	2.886
SE Kurtosis	.	0.061	0.067	0.061	0.062

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	6509	6509	6509	6509	6509
Minimum	18.594	23.443	20.459	21.391	9.269
Maximum	701.351	732.029	718.136	714.126	702.004
Mean	427.006	427.292	426.937	426.869	427.413
Standard Dev	87.665	88.032	87.357	87.789	87.155
Skewness(G1)	-0.167	-0.218	-0.208	-0.169	-0.183
SE Skewness	0.030	0.030	0.030	0.030	0.030
Kurtosis(G2)	0.172	0.283	0.243	0.150	0.224
SE Kurtosis	0.061	0.061	0.061	0.061	0.061

Table C29 - Korea

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	5166	5170	5158	5157	5158
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	-0.724	-0.225	-0.335	-0.419	-1.039
Standard Dev	0.948	0.897	0.965	0.931	0.950
Skewness(G1)	0.247	-0.277	0.012	-0.225	0.103
SE Skewness	0.034	0.034	0.034	0.034	0.034
Kurtosis(G2)	0.333	3.451	0.454	-0.074	-0.273
SE Kurtosis	0.068	0.068	0.068	0.068	0.068

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	5157	5172	5172	5166	5167
Minimum	-1.259	-4.193	-4.920	-1.526	1.000
Maximum	3.027	2.948	2.955	1.202	6.000
Mean	-0.205	-0.287	-0.189	0.110	3.687
Standard Dev	0.901	0.776	0.920	0.964	1.257
Skewness(G1)	0.417	-0.166	-0.099	-0.345	-0.050
SE Skewness	0.034	0.034	0.034	0.034	0.034
Kurtosis(G2)	-0.394	0.610	0.511	-1.070	-0.460
SE Kurtosis	0.068	0.068	0.068	0.068	0.068

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	5176	5171	5113	5168	5112
Minimum	2.000	-4.273	16.000	-3.331	1.000
Maximum	3.000	0.696	90.000	2.362	2.000

Mean	2.989	-0.124	49.988	-0.011	1.000
Standard Dev	0.103	0.833	13.420	0.816	0.014
Skewness(G1)	-9.460	-0.755	0.189	-0.143	71.498
SE Skewness	0.034	0.034	0.034	0.034	0.034
Kurtosis(G2)	87.525	0.198	0.063	-0.044	5112.000
SE Kurtosis	0.068	0.068	0.068	0.068	0.068

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	5176	5176	5176	5176	5176
Minimum	208.818	169.934	142.613	187.838	172.918
Maximum	771.193	793.666	788.817	779.026	780.611
Mean	521.695	521.137	521.964	522.438	522.361
Standard Dev	90.548	90.176	89.990	90.347	90.609
Skewness(G1)	-0.233	-0.297	-0.241	-0.245	-0.223
SE Skewness	0.034	0.034	0.034	0.034	0.034
Kurtosis(G2)	-0.152	-0.088	-0.086	-0.096	-0.069
SE Kurtosis	0.068	0.068	0.068	0.068	0.068

Table C30 - Kirgizstan

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	5290	5825	5285	5349	5411
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.670	-0.160	0.723	0.804	0.899
Standard Dev	0.778	0.986	0.951	0.953	0.888
Skewness(G1)	-0.098	0.051	0.092	0.136	-0.005
SE Skewness	0.034	0.032	0.034	0.033	0.033
Kurtosis(G2)	-0.118	1.193	0.101	0.334	0.058
SE Kurtosis	0.067	0.064	0.067	0.067	0.067

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	5287	5883	5892	5562	5713
Minimum	-1.259	-4.182	-5.978	-1.451	1.000
Maximum	3.027	1.563	3.388	1.066	6.000
Mean	1.283	-2.146	-1.398	0.148	2.271
Standard Dev	1.011	0.974	1.077	0.795	1.239
Skewness(G1)	-0.249	-0.110	-0.269	-0.468	1.067
SE Skewness	0.034	0.032	0.032	0.033	0.032
Kurtosis(G2)	0.014	-0.149	0.805	-0.652	0.839
SE Kurtosis	0.067	0.064	0.064	0.066	0.065

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	5904	5794	5387	5882	5566
Minimum	2.000	-4.321	16.000	-4.343	1.000
Maximum	3.000	1.528	90.000	2.552	3.000
Mean	2.247	-1.149	47.088	-0.578	1.032
Standard Dev	0.431	1.073	18.017	0.888	0.219
Skewness(G1)	1.175	0.453	0.728	-0.056	7.389
SE Skewness	0.032	0.032	0.033	0.032	0.033
Kurtosis(G2)	-0.620	0.523	-0.496	0.034	57.284
SE Kurtosis	0.064	0.064	0.067	0.064	0.066

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	5904	5904	5904	5904	5904
Minimum	6.005	23.443	14.118	21.391	14.118
Maximum	669.460	632.441	659.110	670.300	648.853
Mean	326.429	326.377	326.674	326.158	326.028
Standard Dev	83.214	82.709	83.067	82.999	82.631
Skewness(G1)	0.283	0.270	0.267	0.260	0.263
SE Skewness	0.032	0.032	0.032	0.032	0.032
Kurtosis(G2)	0.599	0.463	0.539	0.493	0.591
SE Kurtosis	0.064	0.064	0.064	0.064	0.064

Table C31 - Latvia

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4660	4696	4675	4683	4684
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.024	-0.006	0.252	0.017	0.266
Standard Dev	0.702	0.823	0.769	0.756	0.823
Skewness(G1)	0.281	0.305	0.007	-0.364	0.031
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	0.972	1.944	0.932	1.374	1.007
SE Kurtosis	0.072	0.071	0.072	0.072	0.072

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4676	4704	4704	4683	4681
Minimum	-1.259	-3.608	-3.075	-1.478	1.000
Maximum	3.027	2.474	4.016	1.131	6.000
Mean	0.158	-0.742	-0.128	0.394	3.676
Standard Dev	0.872	0.814	0.884	0.833	1.306
Skewness(G1)	0.086	0.011	0.156	-0.855	0.024
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.191	0.020	0.326	-0.251	-0.573
SE Kurtosis	0.072	0.071	0.071	0.072	0.072

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4719	4695	4507	4691	4596
Minimum	2.000	-3.140	16.000	-3.053	1.000
Maximum	3.000	0.868	90.000	2.606	3.000
Mean	2.040	0.016	49.345	0.048	1.089
Standard Dev	0.195	0.930	16.629	0.880	0.305
Skewness(G1)	4.721	-0.545	0.339	0.001	3.463
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	20.299	-1.015	-0.652	-0.659	12.028
SE Kurtosis	0.071	0.071	0.073	0.071	0.072

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4719	4719	4719	4719	4719
Minimum	191.941	125.735	154.642	164.992	94.963
Maximum	809.798	767.650	827.328	784.155	772.033
Mean	493.662	493.619	493.498	494.561	493.546
Standard Dev	83.438	83.510	83.739	83.876	83.897
Skewness(G1)	-0.062	-0.052	-0.073	-0.116	-0.091
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.002	-0.192	0.021	-0.058	0.070
SE Kurtosis	0.071	0.071	0.071	0.071	0.071

Table C32 - Liechtenstein

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	329	339	330	331	331
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.088	-0.115	0.047	-0.043	-0.141
Standard Dev	1.075	1.046	1.015	0.877	0.958
Skewness(G1)	-0.079	0.148	0.072	0.074	-0.133
SE Skewness	0.134	0.132	0.134	0.134	0.134
Kurtosis(G2)	-0.000	2.451	0.755	1.181	0.583
SE Kurtosis	0.268	0.264	0.268	0.267	0.267

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	330	338	338	334	331
Minimum	-1.259	-2.951	-3.111	-1.575	1.000

Maximum	3.027	2.244	3.180	1.206	6.000
Mean	-0.038	0.384	0.347	0.051	3.502
Standard Dev	0.982	0.771	0.846	0.994	1.445
Skewness(G1)	0.353	0.254	0.314	-0.273	0.049
SE Skewness	0.134	0.133	0.133	0.133	0.134
Kurtosis(G2)	-0.298	1.123	1.593	-1.149	-0.852
SE Kurtosis	0.268	0.265	0.265	0.266	0.267

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	339	337	335	337	335
Minimum	2.000	-2.188	16.000	-2.495	1.000
Maximum	3.000	1.282	88.000	2.752	3.000
Mean	2.112	0.252	51.161	0.190	1.603
Standard Dev	0.316	0.972	15.500	0.894	0.844
Skewness(G1)	2.470	-0.322	0.031	-0.094	0.859
SE Skewness	0.132	0.133	0.133	0.133	0.133
Kurtosis(G2)	4.126	-1.036	-0.275	-0.105	-1.049
SE Kurtosis	0.264	0.265	0.266	0.265	0.266

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	339	339	339	339	339
Minimum	219.542	267.564	233.529	248.915	239.124
Maximum	782.569	813.994	793.946	783.316	780.705
Mean	521.861	523.858	519.531	522.287	523.731
Standard Dev	95.930	98.384	96.984	96.449	97.031
Skewness(G1)	-0.119	-0.098	-0.081	-0.074	-0.127
SE Skewness	0.132	0.132	0.132	0.132	0.132
Kurtosis(G2)	-0.093	-0.293	-0.229	-0.120	-0.170
SE Kurtosis	0.264	0.264	0.264	0.264	0.264

Table C33 - Lithuania

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4685	4725	4704	4707	4711
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	-0.237	0.004	0.233	0.214	0.105
Standard Dev	0.783	0.809	0.829	0.801	0.797
Skewness(G1)	0.396	-0.121	0.242	0.048	-0.051
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	1.026	2.564	0.949	1.043	1.182
SE Kurtosis	0.072	0.071	0.071	0.071	0.071

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4707	4737	4737	4667	4706
Minimum	-1.259	-3.413	-4.991	-1.403	1.000
Maximum	3.027	2.323	3.644	1.031	6.000
Mean	-0.005	-0.569	-0.200	0.160	3.167
Standard Dev	0.901	0.782	0.928	0.899	1.350
Skewness(G1)	0.363	-0.013	0.075	-0.537	0.236
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.069	0.480	0.798	-1.075	-0.543
SE Kurtosis	0.071	0.071	0.071	0.072	0.071

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4744	4734	4560	4721	4628
Minimum	2.000	-4.056	16.000	-3.553	1.000
Maximum	3.000	0.892	90.000	2.594	3.000
Mean	2.000	-0.067	49.593	0.031	1.029
Standard Dev	0.015	0.928	17.874	0.914	0.193
Skewness(G1)	68.877	-0.443	0.243	0.038	7.464
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	4744.000	-0.779	-0.952	-0.749	60.553

SE Kurtosis	0.071	0.071	0.073	0.071	0.072

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4744	4744	4744	4744	4744
Minimum	144.664	165.179	149.606	155.015	144.664
Maximum	801.405	776.695	763.640	786.486	777.721
Mean	486.464	486.552	486.448	486.897	486.259
Standard Dev	89.973	89.807	89.616	90.348	90.385
Skewness(G1)	-0.061	-0.058	-0.068	-0.071	-0.067
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.245	-0.287	-0.296	-0.220	-0.201
SE Kurtosis	0.071	0.071	0.071	0.071	0.071

Table C34 - Luxembourg

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4416	4530	4456	4468	4473
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.238	-0.134	-0.161	-0.233	-0.085
Standard Dev	1.058	1.042	1.033	1.042	1.044
Skewness(G1)	-0.219	-0.214	-0.085	0.052	-0.096
SE Skewness	0.037	0.036	0.037	0.037	0.037
Kurtosis(G2)	-0.062	2.691	0.340	0.031	0.400
SE Kurtosis	0.074	0.073	0.073	0.073	0.073

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4454	4550	4552	4518	4488
Minimum	-1.259	-3.905	-5.970	-1.602	1.000
Maximum	3.027	2.211	3.172	1.229	6.000
Mean	-0.143	0.327	0.337	0.021	3.700
Standard Dev	1.029	0.791	0.937	1.017	1.513
Skewness(G1)	0.558	0.033	0.073	-0.229	-0.050
SE Skewness	0.037	0.036	0.036	0.036	0.037
Kurtosis(G2)	-0.398	0.675	1.692	-1.183	-0.956
SE Kurtosis	0.073	0.073	0.073	0.073	0.073

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4567	4541	4357	4488	4490
Minimum	2.000	-4.109	16.000	-3.296	1.000
Maximum	3.000	1.346	90.000	3.243	3.000
Mean	2.359	0.354	47.687	0.090	1.518
Standard Dev	0.480	1.033	16.617	1.098	0.758
Skewness(G1)	0.587	-0.581	0.233	-0.362	1.057
SE Skewness	0.036	0.036	0.037	0.037	0.037
Kurtosis(G2)	-1.657	-0.426	-0.539	-0.355	-0.456
SE Kurtosis	0.072	0.073	0.074	0.073	0.073

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4567	4567	4567	4567	4567
Minimum	171.799	134.314	152.963	184.108	171.053
Maximum	757.579	767.836	782.476	782.476	792.081
Mean	486.965	487.166	486.982	486.869	486.246
Standard Dev	96.896	96.812	96.333	96.228	96.361
Skewness(G1)	-0.160	-0.125	-0.178	-0.178	-0.147
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.308	-0.305	-0.246	-0.251	-0.265
SE Kurtosis	0.072	0.072	0.072	0.072	0.072

Table C35 - Macao - China

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	2937	4749	2987	2998	2994

Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	-0.145	-0.118	-0.185	-0.191	-0.410
Standard Dev	0.906	0.918	0.921	0.856	0.903
Skewness(G1)	0.106	0.043	-0.076	-0.197	-0.037
SE Skewness	0.045	0.036	0.045	0.045	0.045
Kurtosis(G2)	0.343	1.759	0.952	0.940	0.944
SE Kurtosis	0.090	0.071	0.090	0.089	0.089

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	2982	4754	4754	4721	4732
Minimum	-1.259	-4.229	-4.998	-1.412	1.000
Maximum	3.027	2.478	3.289	1.046	6.000
Mean	0.023	-0.557	-0.733	-0.440	2.391
Standard Dev	0.911	0.851	0.872	0.859	1.225
Skewness(G1)	0.288	-0.174	-0.042	0.339	0.672
SE Skewness	0.045	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.090	0.723	0.666	-1.046	-0.045
SE Kurtosis	0.090	0.071	0.071	0.071	0.071

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4760	4753	4657	4746	4672
Minimum	2.000	-4.327	16.000	-3.754	1.000
Maximum	3.000	0.460	88.000	2.452	3.000
Mean	2.372	-0.422	41.913	-0.905	1.876
Standard Dev	0.483	0.802	13.933	0.885	0.647
Skewness(G1)	0.530	-0.549	0.545	0.232	0.124
SE Skewness	0.035	0.036	0.036	0.036	0.036
Kurtosis(G2)	-1.719	-0.049	0.082	-0.021	-0.649
SE Kurtosis	0.071	0.071	0.072	0.071	0.072

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4760	4760	4760	4760	4760
Minimum	210.217	197.162	221.407	190.076	214.879
Maximum	739.303	781.544	795.624	738.650	775.949
Mean	509.450	509.817	509.292	509.449	509.306
Standard Dev	78.961	78.726	79.298	78.784	79.604
Skewness(G1)	-0.148	-0.164	-0.145	-0.152	-0.169
SE Skewness	0.035	0.035	0.035	0.035	0.035
Kurtosis(G2)	-0.189	-0.128	-0.128	-0.108	-0.110
SE Kurtosis	0.071	0.071	0.071	0.071	0.071

Table C36 - Mexico

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	29715	30862	30112	30175	30205
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.532	0.108	0.380	0.506	0.375
Standard Dev	0.790	0.877	1.044	1.019	0.907
Skewness(G1)	-0.042	0.190	-0.050	-0.059	-0.086
SE Skewness	0.014	0.014	0.014	0.014	0.014
Kurtosis(G2)	0.292	0.966	0.394	0.560	1.016
SE Kurtosis	0.028	0.028	0.028	0.028	0.028

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	30113	30867	30891	30161	30279
Minimum	-1.259	-3.957	-6.541	-1.435	1.000
Maximum	3.027	1.899	3.233	1.081	6.000
Mean	0.744	-1.373	-1.026	-0.314	2.153
Standard Dev	0.955	1.076	1.162	0.892	1.159
Skewness(G1)	0.020	-0.181	-0.112	0.169	0.980
SE Skewness	0.014	0.014	0.014	0.014	0.014

Kurtosis(G2)	0.192	0.061	0.358	-1.146	0.693
SE Kurtosis	0.028	0.028	0.028	0.028	0.028

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	30971	30752	29923	30877	29869
Minimum	2.000	-4.644	16.000	-4.829	1.000
Maximum	3.000	1.081	90.000	2.718	3.000
Mean	2.778	-0.577	43.575	-0.803	1.027
Standard Dev	0.416	1.136	18.568	1.260	0.220
Skewness(G1)	-1.337	-0.000	0.512	0.104	8.400
SE Skewness	0.014	0.014	0.014	0.014	0.014
Kurtosis(G2)	-0.212	-0.608	-0.808	-0.847	70.370
SE Kurtosis	0.028	0.028	0.028	0.028	0.028

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	30971	30971	30971	30971	30971
Minimum	120.233	146.249	90.301	130.957	130.957
Maximum	703.309	740.795	740.795	708.904	728.299
Mean	422.459	422.741	422.943	422.544	422.526
Standard Dev	75.623	75.864	75.964	75.735	75.689
Skewness(G1)	0.079	0.078	0.081	0.079	0.080
SE Skewness	0.014	0.014	0.014	0.014	0.014
Kurtosis(G2)	-0.051	-0.060	-0.025	-0.082	-0.060
SE Kurtosis	0.028	0.028	0.028	0.028	0.028

Table C37 - Montenegro

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4267	4355	4290	4299	4304
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.523	-0.016	0.184	-0.328	0.267
Standard Dev	0.888	1.024	1.152	1.230	0.932
Skewness(G1)	-0.276	0.018	-0.032	0.320	-0.143
SE Skewness	0.037	0.037	0.037	0.037	0.037
Kurtosis(G2)	0.586	1.570	0.064	-0.268	0.844
SE Kurtosis	0.075	0.074	0.075	0.075	0.075

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4249	4412	4415	4358	4313
Minimum	-1.259	-3.854	-6.041	-1.401	1.000
Maximum	3.027	2.459	3.717	1.033	6.000
Mean	0.317	-0.627	-0.316	0.359	2.872
Standard Dev	1.160	0.884	0.989	0.778	1.403
Skewness(G1)	0.340	0.148	0.120	-0.846	0.492
SE Skewness	0.038	0.037	0.037	0.037	0.037
Kurtosis(G2)	-0.483	0.304	0.765	-0.344	-0.416
SE Kurtosis	0.075	0.074	0.074	0.074	0.075

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4455	4410	3890	4408	4302
Minimum	2.000	-4.604	16.000	-3.742	1.000
Maximum	3.000	1.415	90.000	2.649	3.000
Mean	2.998	-0.318	48.887	-0.041	1.113
Standard Dev	0.045	1.134	16.144	0.897	0.446
Skewness(G1)	-22.189	-0.097	0.459	-0.099	3.836
SE Skewness	0.037	0.037	0.039	0.037	0.037
Kurtosis(G2)	490.554	-0.420	-0.380	-0.287	13.062
SE Kurtosis	0.073	0.074	0.078	0.074	0.075

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4455	4455	4455	4455	4455
Minimum	137.484	160.423	116.410	142.613	163.593

Maximum	671.792	698.554	722.705	681.116	671.792
Mean	408.778	409.110	408.759	408.651	408.643
Standard Dev	79.204	79.305	79.321	79.557	79.018
Skewness(G1)	0.117	0.137	0.106	0.149	0.121
SE Skewness	0.037	0.037	0.037	0.037	0.037
Kurtosis(G2)	-0.167	-0.138	-0.128	-0.131	-0.159
SE Kurtosis	0.073	0.073	0.073	0.073	0.073

Table C38 - Netherlands

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4260	4758	4262	4282	4293
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	-0.323	0.055	-0.259	0.089	-0.261
Standard Dev	0.918	0.963	0.889	0.861	0.852
Skewness(G1)	-0.115	-0.161	-0.225	-0.233	-0.259
SE Skewness	0.038	0.035	0.038	0.037	0.037
Kurtosis(G2)	0.257	2.091	0.697	1.041	0.989
SE Kurtosis	0.075	0.071	0.075	0.075	0.075

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4263	4865	4865	4842	4767
Minimum	-1.259	-2.351	-2.978	-1.744	1.000
Maximum	3.027	3.081	3.664	1.268	6.000
Mean	-0.164	0.675	0.267	-0.296	3.349
Standard Dev	0.910	0.762	0.853	1.015	1.487
Skewness(G1)	0.388	0.143	0.301	0.081	0.124
SE Skewness	0.038	0.035	0.035	0.035	0.035
Kurtosis(G2)	-0.404	0.389	0.730	-0.997	-0.870
SE Kurtosis	0.075	0.070	0.070	0.070	0.071

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4870	4863	4734	4838	4787
Minimum	2.000	-4.052	16.000	-3.491	1.000
Maximum	3.000	0.935	88.000	2.890	3.000
Mean	2.275	0.151	52.050	0.292	1.145
Standard Dev	0.447	0.842	15.680	0.884	0.438
Skewness(G1)	1.006	-0.777	0.036	-0.323	3.123
SE Skewness	0.035	0.035	0.036	0.035	0.035
Kurtosis(G2)	-0.988	-0.024	-0.650	0.037	9.079
SE Kurtosis	0.070	0.070	0.071	0.070	0.071

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4871	4871	4871	4871	4871
Minimum	180.844	254.510	238.005	182.056	212.828
Maximum	802.058	798.608	805.135	817.910	791.615
Mean	530.414	531.389	530.512	530.496	530.980
Standard Dev	93.382	93.781	93.481	94.017	94.111
Skewness(G1)	-0.201	-0.159	-0.183	-0.193	-0.176
SE Skewness	0.035	0.035	0.035	0.035	0.035
Kurtosis(G2)	-0.413	-0.452	-0.452	-0.381	-0.481
SE Kurtosis	0.070	0.070	0.070	0.070	0.070

Table C39 - New Zealand

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4354	4776	4360	4363	4367
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	-0.061	-0.016	0.175	0.315	0.128
Standard Dev	0.950	1.047	0.970	0.737	0.944
Skewness(G1)	-0.135	-0.090	-0.053	-0.229	-0.163

SE Skewness	0.037	0.035	0.037	0.037	0.037
Kurtosis(G2)	0.301	1.563	0.718	1.869	0.744
SE Kurtosis	0.074	0.071	0.074	0.074	0.074

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4361	4787	4787	4702	4734
Minimum	-1.259	-2.874	-4.672	-1.798	1.000
Maximum	3.027	2.134	2.947	1.342	6.000
Mean	-0.000	0.334	0.135	-0.114	3.648
Standard Dev	0.901	0.800	0.930	1.086	1.366
Skewness(G1)	0.203	-0.042	0.170	-0.098	-0.048
SE Skewness	0.037	0.035	0.035	0.036	0.036
Kurtosis(G2)	-0.337	0.106	0.682	-1.106	-0.704
SE Kurtosis	0.074	0.071	0.071	0.071	0.071

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4823	4776	4625	4727	4711
Minimum	2.000	-3.973	16.000	-3.199	1.000
Maximum	3.000	0.535	90.000	2.470	3.000
Mean	2.941	-0.104	51.792	0.115	1.376
Standard Dev	0.236	0.786	15.966	0.825	0.733
Skewness(G1)	-3.733	-1.051	0.068	-0.266	1.585
SE Skewness	0.035	0.035	0.036	0.036	0.036
Kurtosis(G2)	11.940	0.740	-0.586	0.107	0.738
SE Kurtosis	0.071	0.071	0.072	0.071	0.071

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4823	4823	4823	4823	4823
Minimum	158.651	187.651	155.854	163.407	149.420
Maximum	887.193	908.360	825.650	842.901	873.019
Mean	532.308	532.691	532.710	532.824	532.885
Standard Dev	106.934	106.863	106.104	107.101	106.743
Skewness(G1)	-0.146	-0.144	-0.164	-0.161	-0.158
SE Skewness	0.035	0.035	0.035	0.035	0.035
Kurtosis(G2)	-0.294	-0.313	-0.284	-0.302	-0.309
SE Kurtosis	0.071	0.071	0.071	0.071	0.071

Table C40 - Norway

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4444	4595	4542	4549	4552
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.050	0.118	-0.104	0.171	0.075
Standard Dev	0.995	1.058	0.929	0.822	0.959
Skewness(G1)	-0.073	-0.468	-0.071	-0.185	-0.142
SE Skewness	0.037	0.036	0.036	0.036	0.036
Kurtosis(G2)	0.065	3.369	0.668	1.495	0.731
SE Kurtosis	0.073	0.072	0.073	0.073	0.073

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4540	4607	4607	4568	4544
Minimum	-1.259	-3.831	-5.762	-1.897	1.000
Maximum	3.027	3.303	3.963	1.344	6.000
Mean	-0.233	0.742	0.524	0.295	3.903
Standard Dev	0.981	0.825	0.917	1.092	1.385
Skewness(G1)	0.653	-0.019	-0.044	-0.615	-0.222
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.141	1.952	3.081	-0.811	-0.673
SE Kurtosis	0.073	0.072	0.072	0.072	0.073

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4692	4597	4510	4602	4585

Minimum	2.000	-3.877	16.000	-5.670	1.000
Maximum	3.000	0.705	90.000	3.009	3.000
Mean	2.003	0.109	53.108	0.423	1.095
Standard Dev	0.051	0.810	15.336	0.755	0.386
Skewness(G1)	19.704	-1.310	0.134	-0.260	4.198
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	386.416	1.871	-0.641	1.615	16.761
SE Kurtosis	0.071	0.072	0.073	0.072	0.072

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4692	4692	4692	4692	4692
Minimum	129.558	130.770	161.262	143.732	98.973
Maximum	803.923	790.216	798.142	848.495	828.820
Mean	486.429	486.932	487.119	486.783	487.387
Standard Dev	96.221	94.968	94.634	95.157	95.949
Skewness(G1)	-0.100	-0.161	-0.112	-0.108	-0.153
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.099	-0.002	-0.102	-0.059	0.046
SE Kurtosis	0.071	0.071	0.071	0.071	0.071

Table C41 - Poland

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	5497	5521	5518	5517	5521
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.085	0.298	0.102	-0.203	0.020
Standard Dev	0.831	0.939	0.886	0.820	0.812
Skewness(G1)	0.134	0.195	0.023	0.157	-0.048
SE Skewness	0.033	0.033	0.033	0.033	0.033
Kurtosis(G2)	0.573	1.814	0.844	0.902	1.352
SE Kurtosis	0.066	0.066	0.066	0.066	0.066

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	5505	5533	5533	5484	5500
Minimum	-1.259	-3.676	-5.808	-1.760	1.000
Maximum	3.027	2.233	3.809	1.268	6.000
Mean	0.095	-0.772	-0.169	0.144	3.260
Standard Dev	0.967	0.854	1.034	1.005	1.378
Skewness(G1)	0.191	0.070	0.009	-0.483	0.301
SE Skewness	0.033	0.033	0.033	0.033	0.033
Kurtosis(G2)	-0.424	0.301	0.742	-0.796	-0.615
SE Kurtosis	0.066	0.066	0.066	0.066	0.066

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	5547	5528	5380	5520	5449
Minimum	2.000	-3.944	16.000	-3.085	1.000
Maximum	3.000	0.862	90.000	2.947	3.000
Mean	2.022	0.173	45.315	-0.237	1.003
Standard Dev	0.148	0.938	15.326	0.903	0.068
Skewness(G1)	6.464	-1.017	0.507	0.407	26.525
SE Skewness	0.033	0.033	0.033	0.033	0.033
Kurtosis(G2)	39.794	-0.073	-0.110	-0.141	736.871
SE Kurtosis	0.066	0.066	0.067	0.066	0.066

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	5547	5547	5547	5547	5547
Minimum	198.654	206.114	163.314	202.384	203.410
Maximum	822.852	789.843	820.521	830.312	824.344
Mean	503.022	503.700	503.261	503.319	503.125
Standard Dev	91.227	90.918	90.902	90.875	91.076
Skewness(G1)	0.022	-0.005	0.005	0.019	0.014
SE Skewness	0.033	0.033	0.033	0.033	0.033

Kurtosis(G2)	-0.285	-0.289	-0.202	-0.258	-0.197
SE Kurtosis	0.066	0.066	0.066	0.066	0.066

Table C42 - Portugal

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4025	5089	4001	4018	4021
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.306	0.213	0.330	0.115	0.379
Standard Dev	0.818	0.906	0.973	0.885	0.948
Skewness(G1)	-0.254	0.060	0.002	-0.213	-0.068
SE Skewness	0.039	0.034	0.039	0.039	0.039
Kurtosis(G2)	1.080	1.300	0.820	1.123	0.725
SE Kurtosis	0.077	0.069	0.077	0.077	0.077

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4007	5096	5096	5088	5064
Minimum	-1.259	-3.559	-5.919	-1.442	1.000
Maximum	3.027	2.339	3.532	1.079	6.000
Mean	0.440	-0.158	0.065	-0.099	2.976
Standard Dev	0.924	0.882	1.071	0.946	1.398
Skewness(G1)	0.045	0.059	0.064	-0.126	0.429
SE Skewness	0.039	0.034	0.034	0.034	0.034
Kurtosis(G2)	0.028	-0.006	0.285	-1.310	-0.481
SE Kurtosis	0.077	0.069	0.069	0.069	0.069

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	5109	5096	4956	5091	5053
Minimum	2.000	-4.047	16.000	-3.448	1.000
Maximum	3.000	1.102	90.000	3.349	3.000
Mean	2.536	0.266	42.013	-0.585	1.083
Standard Dev	0.499	0.970	16.301	1.277	0.370
Skewness(G1)	-0.143	-0.706	0.882	0.357	4.575
SE Skewness	0.034	0.034	0.035	0.034	0.034
Kurtosis(G2)	-1.980	-0.665	0.207	-0.659	19.894
SE Kurtosis	0.069	0.069	0.070	0.069	0.069

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	5109	5109	5109	5109	5109
Minimum	155.201	173.851	107.645	134.500	120.700
Maximum	756.367	734.081	767.836	742.660	760.097
Mean	478.689	479.450	478.527	478.590	479.617
Standard Dev	86.807	87.513	87.395	87.035	87.098
Skewness(G1)	-0.100	-0.096	-0.115	-0.111	-0.121
SE Skewness	0.034	0.034	0.034	0.034	0.034
Kurtosis(G2)	-0.330	-0.355	-0.238	-0.290	-0.273
SE Kurtosis	0.069	0.069	0.069	0.069	0.069

Table C43 - Qatar

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	5762	5935	5788	5796	5809
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.584	-0.098	0.368	0.518	0.417
Standard Dev	1.043	1.280	1.168	1.165	1.127
Skewness(G1)	-0.547	-0.195	-0.175	-0.229	-0.276
SE Skewness	0.032	0.032	0.032	0.032	0.032
Kurtosis(G2)	0.387	1.469	0.192	0.207	0.303
SE Kurtosis	0.065	0.064	0.064	0.064	0.064

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01

N of cases	5786	5983	5985	5722	5863
Minimum	-1.259	-3.511	-5.336	-1.547	1.000
Maximum	3.027	1.947	2.568	1.250	6.000
Mean	0.880	0.104	-0.354	-0.116	3.001
Standard Dev	1.115	0.918	1.026	0.940	1.548
Skewness(G1)	-0.195	0.102	0.336	0.006	0.421
SE Skewness	0.032	0.032	0.032	0.032	0.032
Kurtosis(G2)	-0.310	-0.031	1.130	-1.006	-0.776
SE Kurtosis	0.064	0.063	0.063	0.065	0.064

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	6265	5917	3679	5963	5718
Minimum	2.000	-3.698	16.000	-3.431	1.000
Maximum	3.000	0.311	90.000	2.505	3.000
Mean	2.774	-0.617	61.670	0.203	1.576
Standard Dev	0.418	0.907	12.970	0.942	0.776
Skewness(G1)	-1.312	-0.736	-0.611	-0.801	0.894
SE Skewness	0.031	0.032	0.040	0.032	0.032
Kurtosis(G2)	-0.280	0.078	0.582	0.547	-0.769
SE Kurtosis	0.062	0.064	0.081	0.063	0.065

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	6265	6265	6265	6265	6265
Minimum	103.542	121.166	87.597	127.693	121.166
Maximum	718.415	718.415	725.875	709.837	744.525
Mean	348.994	349.043	348.916	349.621	348.845
Standard Dev	81.877	82.761	82.993	82.892	82.097
Skewness(G1)	0.665	0.690	0.689	0.677	0.681
SE Skewness	0.031	0.031	0.031	0.031	0.031
Kurtosis(G2)	0.805	0.754	0.820	0.813	0.825
SE Kurtosis	0.062	0.062	0.062	0.062	0.062

Table C44 - Romanian

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	5065	5100	5073	5074	5080
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.340	-0.335	0.219	0.323	0.374
Standard Dev	0.810	1.041	0.942	0.933	0.812
Skewness(G1)	-0.083	0.090	0.120	0.062	0.183
SE Skewness	0.034	0.034	0.034	0.034	0.034
Kurtosis(G2)	0.621	1.850	0.661	0.851	1.066
SE Kurtosis	0.069	0.069	0.069	0.069	0.069

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	5072	5113	5114	5038	5077
Minimum	-1.259	-3.548	-5.642	-1.795	1.000
Maximum	3.027	2.151	3.660	1.464	6.000
Mean	0.648	-1.141	-0.691	0.495	3.018
Standard Dev	0.996	0.947	1.169	0.993	1.410
Skewness(G1)	-0.029	-0.107	-0.286	-0.736	0.372
SE Skewness	0.034	0.034	0.034	0.034	0.034
Kurtosis(G2)	0.027	0.008	0.728	-0.287	-0.567
SE Kurtosis	0.069	0.068	0.068	0.069	0.069

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	5118	5079	4736	5110	5111
Minimum	2.000	-4.262	16.000	-4.636	1.000
Maximum	2.000	1.078	90.000	2.600	3.000
Mean	2.000	-0.551	43.391	-0.364	1.001
Standard Dev	0.000	1.295	16.249	0.947	0.048
Skewness(G1)	.	-0.305	0.567	-0.041	41.251

SE Skewness	.	0.034	0.036	0.034	0.034
Kurtosis(G2)	.	-0.812	-0.363	0.286	1700.331
SE Kurtosis	.	0.069	0.071	0.068	0.068

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	5118	5118	5118	5118	5118
Minimum	155.854	133.754	172.452	162.195	172.452
Maximum	681.676	723.824	688.203	693.985	746.949
Mean	416.262	416.456	416.948	417.098	416.272
Standard Dev	80.913	81.117	81.617	80.919	81.497
Skewness(G1)	0.183	0.224	0.194	0.186	0.219
SE Skewness	0.034	0.034	0.034	0.034	0.034
Kurtosis(G2)	-0.229	-0.176	-0.205	-0.166	-0.169
SE Kurtosis	0.068	0.068	0.068	0.068	0.068

Table C45 - Russian Federation

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	5641	5777	5637	5650	5650
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.160	-0.014	0.512	0.583	0.438
Standard Dev	0.735	0.992	0.887	0.776	0.836
Skewness(G1)	0.324	-0.002	0.159	0.448	0.146
SE Skewness	0.033	0.032	0.033	0.033	0.033
Kurtosis(G2)	0.449	1.218	0.513	1.082	0.852
SE Kurtosis	0.065	0.064	0.065	0.065	0.065

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	5634	5791	5791	5746	5766
Minimum	-1.259	-3.708	-4.544	-1.612	1.000
Maximum	3.027	1.540	3.188	1.363	6.000
Mean	0.554	-1.156	-0.409	0.587	3.483
Standard Dev	0.968	0.781	0.919	0.851	1.348
Skewness(G1)	-0.066	-0.065	0.068	-0.811	0.141
SE Skewness	0.033	0.032	0.032	0.032	0.032
Kurtosis(G2)	-0.077	0.384	0.377	-0.036	-0.685
SE Kurtosis	0.065	0.064	0.064	0.065	0.064

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	5799	5774	5621	5785	5714
Minimum	2.000	-4.113	16.000	-3.293	1.000
Maximum	3.000	0.915	90.000	2.329	3.000
Mean	2.665	-0.212	51.333	-0.052	1.146
Standard Dev	0.472	1.034	17.094	0.791	0.478
Skewness(G1)	-0.697	-0.294	0.158	0.073	3.250
SE Skewness	0.032	0.032	0.033	0.032	0.032
Kurtosis(G2)	-1.514	-0.971	-1.038	-0.590	9.230
SE Kurtosis	0.064	0.064	0.065	0.064	0.065

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	5799	5799	5799	5799	5799
Minimum	169.002	143.638	105.407	167.883	135.339
Maximum	774.830	789.750	775.763	764.573	765.785
Mean	481.379	481.733	481.433	481.703	481.259
Standard Dev	89.850	90.561	89.876	89.908	89.141
Skewness(G1)	0.037	-0.009	0.001	0.017	-0.011
SE Skewness	0.032	0.032	0.032	0.032	0.032
Kurtosis(G2)	-0.192	-0.114	-0.161	-0.150	-0.124
SE Kurtosis	0.064	0.064	0.064	0.064	0.064

Table C46 - Serbia

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4537	4757	4547	4563	4570
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.247	0.053	0.000	-0.522	0.075
Standard Dev	0.934	0.978	1.047	1.166	0.916
Skewness(G1)	-0.223	0.173	0.086	0.431	-0.114
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	0.466	1.937	0.317	-0.134	0.779
SE Kurtosis	0.073	0.071	0.073	0.072	0.072

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4545	4789	4789	4727	4731
Minimum	-1.259	-3.677	-5.412	-1.395	1.000
Maximum	3.027	2.385	3.681	1.026	6.000
Mean	0.036	-0.674	-0.351	0.198	2.755
Standard Dev	1.068	0.820	0.957	0.860	1.325
Skewness(G1)	0.496	0.118	0.002	-0.610	0.538
SE Skewness	0.036	0.035	0.035	0.036	0.036
Kurtosis(G2)	-0.285	0.585	0.717	-0.888	-0.216
SE Kurtosis	0.073	0.071	0.071	0.071	0.071

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4798	4777	4645	4786	4709
Minimum	2.000	-4.048	16.000	-3.221	1.000
Maximum	3.000	1.240	90.000	2.568	3.000
Mean	2.990	-0.138	48.510	-0.129	1.149
Standard Dev	0.097	1.113	16.285	0.937	0.493
Skewness(G1)	-10.069	-0.135	0.472	0.211	3.226
SE Skewness	0.035	0.035	0.036	0.035	0.036
Kurtosis(G2)	99.419	-0.957	-0.142	-0.298	8.889
SE Kurtosis	0.071	0.071	0.072	0.071	0.071

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4798	4798	4798	4798	4798
Minimum	125.921	137.484	124.057	155.201	157.998
Maximum	690.907	715.618	710.489	715.991	701.164
Mean	436.764	436.861	436.925	436.808	437.296
Standard Dev	84.898	84.706	84.402	83.699	84.597
Skewness(G1)	-0.040	-0.023	-0.015	-0.002	-0.035
SE Skewness	0.035	0.035	0.035	0.035	0.035
Kurtosis(G2)	-0.089	-0.090	-0.232	-0.134	-0.228
SE Kurtosis	0.071	0.071	0.071	0.071	0.071

Table C47 - Slovakia

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4660	4678	4664	4667	4671
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.146	0.111	-0.165	-0.214	-0.124
Standard Dev	0.829	0.852	0.934	0.957	0.926
Skewness(G1)	0.026	0.248	-0.103	-0.136	-0.040
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	1.034	1.547	0.715	0.296	0.778
SE Kurtosis	0.072	0.072	0.072	0.072	0.072

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4661	4728	4728	4715	4704
Minimum	-1.259	-3.770	-5.619	-1.389	1.000
Maximum	3.027	2.182	3.610	1.020	6.000
Mean	-0.033	-0.811	-0.316	0.317	3.379
Standard Dev	0.986	0.792	0.915	0.812	1.212

Skewness(G1)	0.384	0.091	-0.184	-0.828	0.131
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.358	0.399	1.662	-0.477	-0.167
SE Kurtosis	0.072	0.071	0.071	0.071	0.071

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4731	4726	4526	4723	4682
Minimum	2.000	-4.029	16.000	-4.567	1.000
Maximum	3.000	1.063	90.000	2.808	3.000
Mean	2.636	-0.056	47.502	-0.123	1.006
Standard Dev	0.481	1.062	15.796	0.900	0.093
Skewness(G1)	-0.564	-0.529	0.397	0.267	16.860
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-1.683	-0.397	-0.508	0.129	310.343
SE Kurtosis	0.071	0.071	0.073	0.071	0.072

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4731	4731	4731	4731	4731
Minimum	164.339	167.323	178.140	127.040	159.677
Maximum	784.994	790.029	772.219	792.827	794.692
Mean	491.065	491.841	491.300	490.623	491.253
Standard Dev	93.015	92.467	92.898	92.277	92.925
Skewness(G1)	-0.063	-0.073	-0.064	-0.089	-0.061
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.167	-0.210	-0.273	-0.090	-0.238
SE Kurtosis	0.071	0.071	0.071	0.071	0.071

Table C48 - Slovenia

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	5950	6357	5973	5988	6007
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.241	-0.171	-0.092	-0.054	0.197
Standard Dev	0.869	0.938	0.998	0.953	0.880
Skewness(G1)	-0.022	0.095	0.049	0.136	-0.031
SE Skewness	0.032	0.031	0.032	0.032	0.032
Kurtosis(G2)	0.552	1.973	0.596	0.794	0.959
SE Kurtosis	0.063	0.061	0.063	0.063	0.063

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	5972	6561	6562	6515	6517
Minimum	-1.259	-3.627	-2.975	-1.439	1.000
Maximum	3.027	3.288	4.437	1.086	6.000
Mean	0.210	0.147	0.284	0.102	2.944
Standard Dev	0.970	0.803	0.882	0.907	1.263
Skewness(G1)	0.239	0.235	0.169	-0.367	0.429
SE Skewness	0.032	0.030	0.030	0.030	0.030
Kurtosis(G2)	-0.144	0.578	0.631	-1.124	-0.096
SE Kurtosis	0.063	0.060	0.060	0.061	0.061

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	6595	6560	6387	6554	6486
Minimum	2.000	-3.068	16.000	-3.393	1.000
Maximum	3.000	0.761	90.000	3.118	3.000
Mean	2.993	0.223	47.833	0.011	1.123
Standard Dev	0.084	0.744	15.705	0.862	0.384
Skewness(G1)	-11.721	-1.022	0.386	0.162	3.278
SE Skewness	0.030	0.030	0.031	0.030	0.030
Kurtosis(G2)	135.430	-0.029	-0.588	-0.304	10.596
SE Kurtosis	0.060	0.060	0.061	0.060	0.061

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE

N of cases	6595	6595	6595	6595	6595
Minimum	201.545	196.043	154.082	191.381	199.027
Maximum	822.573	830.872	822.573	821.547	811.290
Mean	494.344	494.525	493.783	493.782	494.510
Standard Dev	96.730	96.675	97.368	96.798	96.543
Skewness(G1)	0.095	0.095	0.070	0.088	0.072
SE Skewness	0.030	0.030	0.030	0.030	0.030
Kurtosis(G2)	-0.346	-0.315	-0.351	-0.344	-0.312
SE Kurtosis	0.060	0.060	0.060	0.060	0.060

Table C49 - Spain

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	19236	19516	19263	19301	19321
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.011	-0.038	-0.044	-0.351	-0.018
Standard Dev	1.020	1.068	1.003	0.986	0.951
Skewness(G1)	-0.141	-0.165	-0.013	0.040	-0.090
SE Skewness	0.018	0.018	0.018	0.018	0.018
Kurtosis(G2)	0.047	1.296	0.566	0.117	0.743
SE Kurtosis	0.035	0.035	0.035	0.035	0.035

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	19264	19540	19542	19465	19395
Minimum	-1.259	-4.116	-6.245	-1.442	1.000
Maximum	3.027	2.180	3.306	1.076	6.000
Mean	-0.156	-0.158	0.144	0.174	3.685
Standard Dev	0.981	0.704	0.803	0.864	1.315
Skewness(G1)	0.566	0.165	0.120	-0.509	0.067
SE Skewness	0.018	0.018	0.018	0.018	0.018
Kurtosis(G2)	-0.184	0.517	1.198	-0.875	-0.632
SE Kurtosis	0.035	0.035	0.035	0.035	0.035

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	19604	19533	19084	19499	19367
Minimum	2.000	-4.384	16.000	-5.069	1.000
Maximum	3.000	1.190	90.000	2.814	3.000
Mean	2.000	0.313	46.320	-0.158	1.089
Standard Dev	0.019	0.936	17.343	1.031	0.406
Skewness(G1)	52.896	-0.596	0.593	0.116	4.421
SE Skewness	0.017	0.018	0.018	0.018	0.018
Kurtosis(G2)	2796.285	-0.527	-0.468	-0.625	17.730
SE Kurtosis	0.035	0.035	0.035	0.035	0.035

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	19604	19604	19604	19604	19604
Minimum	23.722	23.443	23.722	23.722	23.722
Maximum	920.482	924.212	884.116	883.183	952.187
Mean	504.448	504.528	504.516	504.170	504.891
Standard Dev	86.537	86.695	86.953	87.283	87.216
Skewness(G1)	-0.189	-0.184	-0.206	-0.217	-0.187
SE Skewness	0.017	0.017	0.017	0.017	0.017
Kurtosis(G2)	0.013	0.080	0.031	0.032	0.051
SE Kurtosis	0.035	0.035	0.035	0.035	0.035

Table C50 - Sweden

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4267	4388	4276	4286	4291
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.018	-0.048	-0.010	0.265	-0.049
Standard Dev	1.034	1.012	0.901	0.798	0.868

Skewness(G1)	-0.029	-0.325	0.033	-0.104	-0.167
SE Skewness	0.037	0.037	0.037	0.037	0.037
Kurtosis(G2)	0.017	2.364	0.946	1.448	1.071
SE Kurtosis	0.075	0.074	0.075	0.075	0.075

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4277	4409	4409	4382	4366
Minimum	-1.259	-3.427	-5.479	-1.926	1.000
Maximum	3.027	2.850	3.298	1.422	6.000
Mean	0.035	0.681	0.200	0.096	3.840
Standard Dev	0.896	0.746	0.846	1.130	1.368
Skewness(G1)	0.205	-0.104	0.192	-0.332	-0.127
SE Skewness	0.037	0.037	0.037	0.037	0.037
Kurtosis(G2)	-0.159	0.596	1.179	-0.994	-0.714
SE Kurtosis	0.075	0.074	0.074	0.074	0.074

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4443	4403	4334	4392	4362
Minimum	2.000	-4.007	16.000	-5.421	1.000
Maximum	3.000	0.774	90.000	2.677	3.000
Mean	2.021	-0.144	50.698	0.233	1.158
Standard Dev	0.143	0.896	15.863	0.783	0.478
Skewness(G1)	6.695	-0.587	0.180	-0.344	3.042
SE Skewness	0.037	0.037	0.037	0.037	0.037
Kurtosis(G2)	42.845	-0.219	-0.698	0.709	8.151
SE Kurtosis	0.073	0.074	0.074	0.074	0.074

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4443	4443	4443	4443	4443
Minimum	113.799	152.870	121.259	139.069	110.069
Maximum	797.676	811.197	801.126	820.708	804.856
Mean	504.274	504.353	504.008	504.818	503.719
Standard Dev	94.028	94.543	94.740	94.537	94.463
Skewness(G1)	-0.135	-0.116	-0.133	-0.134	-0.144
SE Skewness	0.037	0.037	0.037	0.037	0.037
Kurtosis(G2)	-0.141	-0.111	-0.029	-0.107	-0.041
SE Kurtosis	0.073	0.073	0.073	0.073	0.073

Table C51 - Switzerland

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	10988	12141	10953	10984	10996
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.100	-0.211	0.126	0.060	-0.031
Standard Dev	0.989	0.944	0.956	0.960	0.911
Skewness(G1)	-0.071	-0.179	-0.213	-0.216	-0.237
SE Skewness	0.023	0.022	0.023	0.023	0.023
Kurtosis(G2)	0.072	2.224	0.729	0.331	0.745
SE Kurtosis	0.047	0.044	0.047	0.047	0.047

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	10948	12174	12175	12088	12066
Minimum	-1.259	-3.830	-5.953	-1.575	1.000
Maximum	3.027	2.244	3.180	1.206	6.000
Mean	0.061	0.095	0.047	-0.215	3.344
Standard Dev	0.960	0.713	0.765	0.967	1.421
Skewness(G1)	0.220	0.122	0.142	0.053	0.119
SE Skewness	0.023	0.022	0.022	0.022	0.022
Kurtosis(G2)	-0.416	1.057	1.907	-1.103	-0.738
SE Kurtosis	0.047	0.044	0.044	0.045	0.045

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG

N of cases	12192	12150	12022	12136	12021
Minimum	2.000	-4.075	16.000	-3.645	1.000
Maximum	3.000	1.282	90.000	2.898	3.000
Mean	2.083	0.285	48.532	0.059	1.320
Standard Dev	0.276	0.997	15.836	0.867	0.651
Skewness(G1)	3.021	-0.525	0.294	-0.020	1.806
SE Skewness	0.022	0.022	0.022	0.022	0.022
Kurtosis(G2)	7.130	-0.470	-0.461	-0.156	1.748
SE Kurtosis	0.044	0.044	0.045	0.044	0.045

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	12192	12192	12192	12192	12192
Minimum	98.880	167.043	131.516	153.056	164.153
Maximum	832.643	808.679	815.113	821.454	826.209
Mean	507.625	508.101	508.118	508.195	508.048
Standard Dev	95.958	96.524	97.037	96.688	96.264
Skewness(G1)	-0.164	-0.146	-0.164	-0.170	-0.154
SE Skewness	0.022	0.022	0.022	0.022	0.022
Kurtosis(G2)	-0.203	-0.213	-0.211	-0.227	-0.220
SE Kurtosis	0.044	0.044	0.044	0.044	0.044

Table C52 - Thailand

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	6159	6165	6168	6168	6169
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.664	0.079	0.626	0.638	0.055
Standard Dev	0.762	0.736	0.878	0.777	0.749
Skewness(G1)	-0.143	0.089	0.242	0.293	0.457
SE Skewness	0.031	0.031	0.031	0.031	0.031
Kurtosis(G2)	0.366	2.169	0.268	0.983	1.482
SE Kurtosis	0.062	0.062	0.062	0.062	0.062

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	6168	6184	6185	6173	6114
Minimum	-1.259	-4.294	-4.420	-1.464	1.000
Maximum	3.027	1.797	2.811	1.075	6.000
Mean	0.964	-1.418	-1.289	-0.095	2.431
Standard Dev	0.755	1.080	1.066	0.873	1.174
Skewness(G1)	0.134	-0.031	0.203	-0.085	0.765
SE Skewness	0.031	0.031	0.031	0.031	0.031
Kurtosis(G2)	1.095	-0.078	-0.074	-1.061	0.389
SE Kurtosis	0.062	0.062	0.062	0.062	0.063

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	6192	6177	5890	6172	5985
Minimum	2.000	-3.830	16.000	-3.814	1.000
Maximum	3.000	0.600	90.000	2.550	3.000
Mean	2.671	-1.167	38.901	-1.237	1.004
Standard Dev	0.470	1.023	16.655	1.185	0.066
Skewness(G1)	-0.730	0.256	0.778	0.571	19.771
SE Skewness	0.031	0.031	0.032	0.031	0.032
Kurtosis(G2)	-1.468	-0.533	-0.322	-0.558	438.376
SE Kurtosis	0.062	0.062	0.064	0.062	0.063

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	6192	6192	6192	6192	6192
Minimum	122.564	141.214	153.802	119.767	144.011
Maximum	768.489	737.717	709.091	728.393	705.174
Mean	429.989	429.954	429.388	429.633	429.688
Standard Dev	82.760	82.705	81.899	82.787	82.823
Skewness(G1)	0.240	0.276	0.249	0.235	0.219

SE Skewness	0.031	0.031	0.031	0.031	0.031
Kurtosis(G2)	-0.000	0.043	-0.060	-0.041	-0.068
SE Kurtosis	0.062	0.062	0.062	0.062	0.062

Table C53 - Tunisia

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4179	4604	4328	4350	4354
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.639	-0.116	0.554	0.645	0.693
Standard Dev	0.862	0.814	0.943	0.834	0.879
Skewness(G1)	-0.301	0.489	-0.063	-0.061	-0.176
SE Skewness	0.038	0.036	0.037	0.037	0.037
Kurtosis(G2)	-0.023	2.346	0.497	1.002	0.722
SE Kurtosis	0.076	0.072	0.074	0.074	0.074

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4329	4628	4628	4508	4370
Minimum	-1.259	-4.223	-5.696	-1.394	1.000
Maximum	3.027	2.171	3.309	1.023	6.000
Mean	0.941	-1.882	-1.702	-0.439	2.050
Standard Dev	0.941	1.163	1.290	0.836	1.106
Skewness(G1)	-0.205	-0.047	-0.284	0.306	1.163
SE Skewness	0.037	0.036	0.036	0.036	0.037
Kurtosis(G2)	0.192	-0.220	0.315	-1.075	1.457
SE Kurtosis	0.074	0.072	0.072	0.073	0.074

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4640	4605	4414	4627	4560
Minimum	2.000	-3.946	16.000	-4.806	1.000
Maximum	3.000	0.687	90.000	2.120	3.000
Mean	2.491	-1.244	37.850	-1.244	1.011
Standard Dev	0.500	1.150	18.740	1.356	0.132
Skewness(G1)	0.037	-0.044	0.733	0.190	12.723
SE Skewness	0.036	0.036	0.037	0.036	0.036
Kurtosis(G2)	-1.999	-0.444	-0.652	-0.766	172.098
SE Kurtosis	0.072	0.072	0.074	0.072	0.073

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4640	4640	4640	4640	4640
Minimum	141.867	107.365	127.880	128.812	130.024
Maximum	692.120	691.187	720.094	660.415	665.637
Mean	384.306	383.931	384.419	384.115	384.199
Standard Dev	81.591	81.730	81.554	81.287	82.184
Skewness(G1)	0.182	0.127	0.174	0.142	0.150
SE Skewness	0.036	0.036	0.036	0.036	0.036
Kurtosis(G2)	-0.111	-0.078	-0.043	-0.099	-0.138
SE Kurtosis	0.072	0.072	0.072	0.072	0.072

Table C54 - Turkey

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4799	4927	4833	4858	4860
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.180	0.046	0.097	0.041	0.449
Standard Dev	0.993	0.995	1.097	1.120	0.922
Skewness(G1)	-0.326	-0.029	-0.028	0.013	0.034
SE Skewness	0.035	0.035	0.035	0.035	0.035
Kurtosis(G2)	0.275	1.330	0.320	-0.062	0.721
SE Kurtosis	0.071	0.070	0.070	0.070	0.070

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4836	4941	4941	4913	4888
Minimum	-1.259	-3.866	-5.877	-1.557	1.000
Maximum	3.027	2.299	2.858	1.270	6.000
Mean	0.797	-1.497	-1.059	-0.001	2.583
Standard Dev	1.005	1.005	1.156	0.942	1.276
Skewness(G1)	-0.078	-0.101	-0.222	-0.154	0.682
SE Skewness	0.035	0.035	0.035	0.035	0.035
Kurtosis(G2)	0.031	-0.127	0.339	-0.946	0.057
SE Kurtosis	0.070	0.070	0.070	0.070	0.070

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4942	4934	4522	4934	4812
Minimum	2.000	-4.332	16.000	-4.417	1.000
Maximum	3.000	1.380	90.000	2.096	3.000
Mean	2.977	-0.654	39.828	-1.241	1.018
Standard Dev	0.151	1.309	15.471	1.081	0.168
Skewness(G1)	-6.297	0.147	0.580	0.374	10.214
SE Skewness	0.035	0.035	0.036	0.035	0.035
Kurtosis(G2)	37.667	-0.723	-0.282	-0.368	108.993
SE Kurtosis	0.070	0.070	0.073	0.070	0.071

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4942	4942	4942	4942	4942
Minimum	126.947	171.706	146.529	115.571	98.973
Maximum	733.055	704.149	698.833	705.361	710.676
Mean	427.922	427.405	427.452	427.589	427.672
Standard Dev	83.047	82.317	82.856	82.867	82.659
Skewness(G1)	0.395	0.355	0.367	0.331	0.359
SE Skewness	0.035	0.035	0.035	0.035	0.035
Kurtosis(G2)	-0.032	-0.097	-0.131	-0.029	-0.104
SE Kurtosis	0.070	0.070	0.070	0.070	0.070

Table C55 - United Kingdom

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	12606	12957	12730	12745	12754
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	-0.005	0.121	0.049	0.422	0.053
Standard Dev	0.914	1.047	0.917	0.725	0.906
Skewness(G1)	-0.058	0.036	0.028	-0.076	-0.171
SE Skewness	0.022	0.022	0.022	0.022	0.022
Kurtosis(G2)	0.568	1.626	0.796	1.751	0.774
SE Kurtosis	0.044	0.043	0.043	0.043	0.043

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	12731	12989	12990	12786	12844
Minimum	-1.259	-4.701	-5.117	-1.615	1.000
Maximum	3.027	3.325	3.956	1.176	6.000
Mean	-0.091	0.389	0.078	-0.162	3.303
Standard Dev	0.927	0.788	0.881	0.972	1.452
Skewness(G1)	0.391	0.273	0.396	-0.036	0.141
SE Skewness	0.022	0.021	0.021	0.022	0.022
Kurtosis(G2)	-0.233	1.031	1.127	-1.268	-0.794
SE Kurtosis	0.043	0.043	0.043	0.043	0.043

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	13152	12961	12399	12806	12751
Minimum	2.000	-3.893	16.000	-3.284	1.000
Maximum	3.000	0.635	90.000	3.006	3.000
Mean	2.991	-0.133	50.064	0.187	1.071
Standard Dev	0.094	0.746	16.228	0.801	0.331

Skewness(G1)	-10.462	-1.075	0.175	-0.044	4.936
SE Skewness	0.021	0.022	0.022	0.022	0.022
Kurtosis(G2)	107.461	0.584	-0.638	-0.028	24.071
SE Kurtosis	0.043	0.043	0.044	0.043	0.043

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	13152	13152	13152	13152	13152
Minimum	66.057	23.443	82.468	88.063	22.790
Maximum	855.116	923.280	895.306	863.601	862.482
Mean	514.344	514.973	514.082	513.971	513.959
Standard Dev	105.943	105.933	105.524	106.046	105.838
Skewness(G1)	-0.114	-0.104	-0.136	-0.114	-0.116
SE Skewness	0.021	0.021	0.021	0.021	0.021
Kurtosis(G2)	-0.199	-0.157	-0.211	-0.219	-0.185
SE Kurtosis	0.043	0.043	0.043	0.043	0.043

Table C56 - United States

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	5481	5542	5467	5475	5481
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.205	0.216	0.392	0.676	0.291
Standard Dev	1.037	1.147	1.018	0.892	0.954
Skewness(G1)	-0.107	0.006	-0.099	-0.087	-0.219
SE Skewness	0.033	0.033	0.033	0.033	0.033
Kurtosis(G2)	0.033	1.605	0.605	1.298	0.945
SE Kurtosis	0.066	0.066	0.066	0.066	0.066

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	5467	5577	5577	5528	5526
Minimum	-1.259	-4.008	-5.883	-1.592	1.000
Maximum	3.027	1.906	2.672	1.165	6.000
Mean	0.485	0.151	-0.114	-0.092	3.200
Standard Dev	1.036	0.798	0.981	1.016	1.472
Skewness(G1)	0.032	0.131	0.321	-0.131	0.179
SE Skewness	0.033	0.033	0.033	0.033	0.033
Kurtosis(G2)	-0.193	0.117	0.596	-1.272	-0.805
SE Kurtosis	0.066	0.066	0.066	0.066	0.066

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	5609	5566	5221	5568	5422
Minimum	2.000	-3.904	16.000	-3.159	1.000
Maximum	3.000	0.408	90.000	2.495	3.000
Mean	2.884	-0.334	52.463	0.129	1.217
Standard Dev	0.320	0.854	16.781	0.908	0.539
Skewness(G1)	-2.406	-0.926	-0.021	-0.210	2.422
SE Skewness	0.033	0.033	0.034	0.033	0.033
Kurtosis(G2)	3.791	0.333	-0.766	-0.203	4.667
SE Kurtosis	0.065	0.066	0.068	0.066	0.067

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	5611	5611	5611	5611	5611
Minimum	163.927	165.793	139.762	160.101	126.607
Maximum	822.053	842.393	830.264	829.891	806.846
Mean	488.292	488.401	488.253	488.606	487.903
Standard Dev	105.567	105.440	105.322	105.520	105.599
Skewness(G1)	0.032	0.032	0.001	0.022	0.008
SE Skewness	0.033	0.033	0.033	0.033	0.033
Kurtosis(G2)	-0.440	-0.431	-0.407	-0.409	-0.403
SE Kurtosis	0.065	0.065	0.065	0.065	0.065

Table C57 - Uruguay

	SCSCIE	SCIEEFF	SCAPPLY	SCHANDS	SCINTACT
N of cases	4188	4757	4161	4193	4203
Minimum	-2.363	-3.768	-2.458	-2.102	-2.510
Maximum	2.244	3.223	2.634	2.908	2.474
Mean	0.362	0.147	0.090	0.144	0.299
Standard Dev	0.868	0.925	0.986	0.970	0.950
Skewness(G1)	-0.136	-0.038	0.048	-0.028	0.023
SE Skewness	0.038	0.036	0.038	0.038	0.038
Kurtosis(G2)	0.601	1.344	0.534	0.690	0.648
SE Kurtosis	0.076	0.071	0.076	0.076	0.076

	SCINVEST	WEALTH	HOMEPOS	CULTPOSS	ST15Q01
N of cases	4163	4791	4792	4712	4680
Minimum	-1.259	-3.862	-6.084	-1.422	1.000
Maximum	3.027	1.903	3.198	1.055	6.000
Mean	0.358	-1.084	-0.682	-0.016	2.658
Standard Dev	0.955	0.959	1.087	0.881	1.318
Skewness(G1)	0.187	-0.121	-0.200	-0.265	0.578
SE Skewness	0.038	0.035	0.035	0.036	0.036
Kurtosis(G2)	-0.028	0.168	0.622	-1.111	-0.226
SE Kurtosis	0.076	0.071	0.071	0.071	0.072

	ISCEDL	HEDRES	HISEI	ESCS	IMMIG
N of cases	4839	4773	4627	4790	4637
Minimum	2.000	-4.354	16.000	-4.276	1.000
Maximum	3.000	0.978	90.000	2.815	3.000
Mean	2.701	-0.367	45.821	-0.395	1.008
Standard Dev	0.458	1.067	18.663	1.220	0.118
Skewness(G1)	-0.879	-0.258	0.420	-0.101	15.633
SE Skewness	0.035	0.035	0.036	0.035	0.036
Kurtosis(G2)	-1.227	-0.536	-0.668	-0.678	251.082
SE Kurtosis	0.070	0.071	0.072	0.071	0.072

	PV1SCIE	PV2SCIE	PV3SCIE	PV4SCIE	PV5SCIE
N of cases	4839	4839	4839	4839	4839
Minimum	118.835	142.893	134.220	126.015	61.954
Maximum	775.110	816.139	729.418	787.978	765.971
Mean	438.123	438.047	437.536	437.700	436.995
Standard Dev	94.595	95.670	94.455	94.707	95.726
Skewness(G1)	-0.023	0.013	-0.027	-0.017	-0.080
SE Skewness	0.035	0.035	0.035	0.035	0.035
Kurtosis(G2)	-0.128	-0.162	-0.227	-0.056	-0.046
SE Kurtosis	0.070	0.070	0.070	0.070	0.070

Appendix D: Correlation Coefficients Between Self-concept, Self-efficacy, Science Literacy and Classroom Environments, by Country

As a common use of appendixes is to present unpublished tests, an additional exploration of the associations between classroom learning and both science self-beliefs and science achievement in PISA is presented below. It is included here only as a propsosed additional step in using large scale measures to help design and implement international studies on educational effectiveness that help to understand the complex structure of education and explain the differences in student outcomes.

Method

PISA 2006 also asked students about the types of science teaching and classrooms they were exposed to in their schools: the focus on applications or models used in teaching (SCAPPLY); the use of hands-on activities in teaching (SCHANDS); if science teaching included and peer or teacher interactions (SCINTACT); and, if science teaching included student investigations (SCINVEST). Four items measuring students' reports on the frequency of these occurrences (i.e., SCAPPLY; SCHANDS; SCINTACT; SCINVEST) in science lessons were included in the student questionnaire. These measures were further summarized and reported on an international scale – mean zero and standard deviation of one with positive scores indicating greater exposure to this type of science instruction in the classroom.

Table D1

Scale Reliabilities for Science Teaching and Learning

Variable	OECD mean	Australia	Canada	Germany	New Zealand	Spain	United States
SCINTACT	0.76	0.80	0.79	0.75	0.79	0.77	0.77
SCHANDS	0.74	0.71	0.72	0.72	0.70	0.74	0.74
SCINVEST	0.75	0.75	0.77	0.77	0.74	0.75	0.75
SCAPPLY	0.76	0.81	0.81	0.73	0.81	0.77	0.76

The scale reliabilities (Table D1) for the indices related to science teaching and learning appear satisfactory across all nations in the study and are typically between 0.70 and 0.80.

A fundamental idea behind social constructivism is that learning about science and doing science is more important than learning science content (Hodson, 2006). The concept of constructivism - that learners build knowledge rather than receive it through transmission from others - incorporates issues such as students' interests, motivation, self-concept or the classroom climate into conditions which are most suited for conceptual change (Duit & Treagust, 2003). Because knowledge of science is said to evolve from the interaction of students' beliefs with classroom instructional practices (Schunk, 2000) an examination of the influence of classroom learning environments on science self-concept, science self-efficacy and science achievement was conducted.

The outcome measures of science self-concept, science self-efficacy and science literacy - as measured by PISA 2006 - were examined at the student level for all participating nations in PISA 2006 through zero order correlations. These three outcome measures were correlated with information collected, again by PISA 2006, on the types of science classroom interactions (i.e., focus on applications (SCAPPLY); hands-on activities (SCHANDS); activities (SCIEACT); interactions (SCINTACT); and, investigations (SCINVEST)). Population statistics (i.e., correlation coefficients) for science literacy were estimated using plausible values and replicate weights as suggested by the OECD (OECD, 2005a). Table D2 outlines the presentation of the correlations among variables.

Table D2

Correlation Coefficients Between Self-concept, Self-efficacy, and Science Literacy and Classroom Environments

Variable	Focus on applications	Hands-on activities	Interactions	Investigations
Science self-efficacy				
Science self-concept				
Science literacy				

Theoretically, constructivist teachers do not instruct in the traditional sense of content delivery (i.e., transmission of content from one to another) but use materials in which learners become actively involved through manipulation of materials and social interaction (Schunk, 2000). Thus, it is theorized that students who are engaged in constructivist type activities in the classroom could potentially show positive and significant correlations with science self-concept, science self-efficacy and science literacy. This is worthwhile, as PISA 2006 has sought to reflect this idea of social constructivism by measuring a student's ability to understand and apply science in their assessment instead of simply assessing science content as reflected in more traditional school curriculum.

Science Teaching and Learning

Focus on model or application in science teaching and learning. The index of focus on model or application in science teaching and learning (SCAPPLY) was derived from the students' responses to how often the following occur in their science school learning: the teacher explains application of phenomena; the teacher uses science to help explain the outside world; the teacher explains the relevance to student lives; and the teacher uses technology to explain relevance. A four point scale with the response categories: "in all lessons", "in most lessons", "in some lessons" and "never or hardly ever" was used. All items were inverted and positive values on this index indicate higher frequencies of interactive science teaching.

Hands-on activities in science teaching and learning. The index of hands-on activities in science teaching and learning (SCHANDS) was derived from the students' responses to how often the following occur in their science school learning: students do practical experiments; student design their own questions; students draw conclusions; and students follow teacher instructions. A four point scale with the response categories: "in all lessons", "in most lessons", "in some lessons" and "never or hardly ever" was used. All items were inverted and positive values on this index indicate higher frequencies of interactive science teaching.

Interaction in science teaching and learning. The index of interaction in science teaching and learning (SCINTACT) was derived from the students' responses to how often the following occur in their science school learning: opportunities to explain ideas; involvement of student opinions; class debate; and student discussions. A four point scale with the response categories: "in all lessons", "in most lessons", "in some lessons" and "never or hardly ever" was used. All items were inverted and positive values on this index indicate higher frequencies of interactive science teaching.

The index of interaction in science teaching and learning (SCINVEST) was derived from the students' responses to how often the following occur in their science school learning: students design own experiments; students choose own investigations; and students investigate to test out ideas. A four point scale with the response categories: "in all lessons", "in most lessons", "in some lessons" and "never or hardly ever" was used. All items were inverted and positive values on this index indicate higher frequencies of interactive science teaching.

Table D3

Descriptive Statistics of Science Teaching and Learning for All Countries in PISA 2006

Variable	Min	Max	Mean	SD	*N*
SCAPPLY	-2.46	2.63	0.17	7.94	369,703
SCHANDS	-2.10	2.91	0.22	7.71	370,716

SCINTACT	-2.51	2.48	0.15	7.63	371,216
SCINVEST	-1.26	3.02	0.38	7.90	369,658

Table D3 shows the mean, range and standard deviation of science teaching and learning for al nations in PISA 2006. Detailed presentation of these variables for all countries that participated in PISA 2006 appears in Appendix B and C.

Science Literacy, Science Self-efficacy, Science Self-concept, and the Classroom Environment

The three outcome measures of science literacy, science self-efficacy and science self-concept were correlated with information collected, again by PISA 2006, on the types of science classroom interactions (i.e., focus on applications (SCAPPLY); hands-on activities (SCHANDS); interactions (SCINTACT); and, investigations (SCINVEST)). These correlations were calculated using the macros made available by the OECD to facilitate SAS analyze of the PISA data sets. They allowed for the computation of the correlation coefficients with appropriately calculated standard errors (i.e., they allowed for the multiple imputations of 5 plausible values and 81 replicate weights) (OECD, 2009a).

Within-country correlations between science achievement, self-efficacy and self-concept and the classroom environment are presented in Table D4. Statistically significant correlation coefficients were determined by building confidence intervals (i.e., for Argentina, science literacy and focus on applications, a value of α equal to 0.05 [-0.05-(1.96*0.02); -0.05+(1.96*0.02)] = -0.09;-0.01. As the coefficient does not include zero, it is significantly different from zero at this level of alpha).

Table D4

Correlation Coefficients Between Self-concept, Self-efficacy, and Science Literacy and Classroom Environments, by Country

Argentina	SCAPPLY	SCHANDS	SCINTACT	SCINVEST
Science literacy	-0.05	-0.18***	-0.01	-0.31***
Self efficacy	0.26***	0.23***	0.17***	0.1***
Self concept	0.3***	0.24***	0.21***	0.28***
Australia				
Science literacy	0.14***	0.28***	0.12***	-0.13***
Self efficacy	0.27***	0.19***	0.22***	0.09***
Self concept	0.31***	0.22***	0.25***	0.15***
Austria				
Science literacy	0.09***	0.2***	-0.11***	-0.31***
Self efficacy	0.25***	0.15***	0.06***	-0.02
Self concept	0.34***	0.19***	0.21***	0.16***
Azerbaijan				
Science literacy	0	-0.02	0.02	-0.16***
Self efficacy	0.26***	0.27***	0.15***	0.12***
Self concept	0.37***	0.33***	0.33***	0.34***
Belgium				
Science literacy	0.17***	0.21***	-0.18***	-0.35***
Self efficacy	0.25***	0.2***	0.05***	0.01
Self concept	0.33***	0.28***	0.19***	0.18***
Bulgaria				
Science literacy	-0.06*	0.03	-0.13***	-0.36***
Self efficacy	0.25***	0.24***	0.19***	0.08***

Self concept	0.32***	0.31***	0.32***	0.31***
Brazil				
Science literacy	-0.01	-0.09***	-0.04	-0.23***
Self efficacy	0.29***	0.27***	0.18***	0.12***
Self concept	0.31***	0.22***	0.28***	0.25***
Canada				
Science literacy	-0.01	-0.09***	-0.04	-0.23***
Self efficacy	0.24***	0.16***	0.14***	0.04***
Self concept	0.3***	0.2***	0.21***	0.1***
Switzerland				
Science literacy	0.08***	0.22***	-0.03	-0.26***
Self efficacy	0.23***	0.19***	0.07***	0.02
Self concept	0.28***	0.22***	0.2***	0.12***
Chile				
Science literacy	0.17***	0.18***	-0.09***	-0.25***
Self efficacy	0.27***	0.22***	0.12***	0.07***
Self concept	0.31***	0.23***	0.22***	0.23***
Columbia				
Science literacy	0	0.07***	-0.12***	-0.25***
Self efficacy	0.25***	0.24***	0.17***	0.14***
Self concept	0.33***	0.24***	0.24***	0.28***
Czech Republic				
Science literacy	0	-0.1***	0.02	-0.18***
Self efficacy	0.22***	0.18***	0.06***	0.05***
Self concept	0.25***	0.2***	0.17***	0.2***
Germany				
Science literacy	-0.01	0.1***	-0.13***	-0.28***
Self efficacy	0.23***	0.16***	0.08***	0.01
Self concept	0.29***	0.21***	0.21***	0.16***
Denmark				
Science literacy	0	0.22***	-0.12***	-0.28***
Self efficacy	0.23***	0.19***	0.17***	0.12***
Self concept	0.28***	0.26***	0.26***	0.22***
Spain				
Science literacy	0.09***	0.27***	0	-0.14***
Self efficacy	0.24***	0.19***	0.05***	0
Self concept	0.26***	0.2***	0.18***	0.15***
Estonia				
Science literacy	0.05***	0.2***	-0.1***	-0.26***
Self efficacy	0.22***	0.17***	0.07***	-0.04
Self concept	0.27***	0.14***	0.18***	0.12***
Finland				
Science literacy	-0.01	0.05*	-0.12***	-0.32***
Self efficacy	0.29***	0.24***	0.13***	0.06***
Self concept	0.3***	0.24***	0.17***	0.11***

France				
Science literacy	0.13***	0.25***	-0.06**	-0.21***
Self efficacy	0.25***	0.25***	0.07***	0.07***
Self concept	0.26***	0.26***	0.18***	0.18***
United Kingdom				
Science literacy	0.08***	0.24***	-0.16***	-0.23***
Self efficacy	0.28***	0.21***	0.14***	0.04***
Self concept	0.3***	0.24***	0.25***	0.2***
Greece				
Science literacy	0.06***	0.25***	-0.01	-0.18***
Self efficacy	0.23***	0.16***	0.02	0.01
Self concept	0.26***	0.17***	0.17***	0.18***
Hong Kong - China				
Science literacy	-0.06**	0.15***	-0.16***	-0.34***
Self efficacy	0.31***	0.26***	0.18***	0.12***
Self concept	0.36***	0.3***	0.32***	0.26***
Croatia				
Science literacy	0.12***	0.25***	-0.02	-0.14***
Self efficacy	0.23***	0.2***	0.06***	0
Self concept	0.31***	0.21***	0.24***	0.23***
Hungary				
Science literacy	0.06**	0.14***	-0.08***	-0.25***
Self efficacy	0.23***	0.21***	0.08***	0.06***
Self concept	0.28***	0.27***	0.21***	0.27***
Indonesia				
Science literacy	-0.02	0.16***	-0.03	-0.25***
Self efficacy	0.25***	0.3***	0.17***	0.15***
Self concept	0.33***	0.27***	0.22***	0.34***
Ireland				
Science literacy	-0.13***	0.03	-0.01	-0.25***
Self efficacy	0.27***	0.23***	0.12***	0.05*
Self concept	0.32***	0.25***	0.24***	0.15***
Israel				
Science literacy	0.05*	0.26***	-0.06**	-0.23***
Self efficacy	0.26***	0.18***	0.16***	0.09***
Self concept	0.28***	0.11***	0.23***	0.12***
Iceland				
Science literacy	0.16***	0.32***	0.08***	-0.18***
Self efficacy	0.31***	0.25***	0.19***	0.18***
Self concept	0.34***	0.28***	0.29***	0.25***
Italy				
Science literacy	-0.03	0.01	-0.01	-0.22***
Self efficacy	0.25***	0.2***	0.09***	0.07***
Self concept	0.29***	0.22***	0.19***	0.24***
Jordan				

Science literacy	-0.11***	0.14***	-0.18***	-0.35***
Self efficacy	0.21***	0.22***	0.13***	0.12***
Self concept	0.35***	0.26***	0.31***	0.25***
Japan				
Science literacy	0.02	-0.05*	-0.06**	-0.19***
Self efficacy	0.26***	0.17***	0.08***	0.12***
Self concept	0.23***	0.15***	0.14***	0.18***
Kyrgyzstan				
Science literacy	0.01	0.22***	-0.21***	-0.11***
Self efficacy	0.29***	0.31***	0.17***	0.17***
Self concept	0.39***	0.39***	0.33***	0.44***
Korea				
Science literacy	-0.14***	-0.3***	-0.14***	-0.33***
Self efficacy	0.21***	0.15***	0.05*	0.05
Self concept	0.2***	0.1***	0.1***	0.11***
Lichtenstein				
Science literacy	0.1***	0.27***	-0.19***	-0.21***
Self efficacy	0.28***	0.25***	0.17***	0.11
Self concept	0.42***	0.34***	0.35***	0.27***
Lithuania				
Science literacy	0.1	0.1	-0.12	-0.28***
Self efficacy	0.19***	0.16***	0.03	0.01
Self concept	0.24***	0.22***	0.2***	0.2***
Luxembourg				
Science literacy	0.05*	0.02	-0.17***	-0.31***
Self efficacy	0.2***	0.18***	0.05*	0.03
Self concept	0.26***	0.22***	0.2***	0.12***
Latvia				
Science literacy	-0.06**	0.18***	-0.17***	-0.35***
Self efficacy	0.26***	0.22***	0.07***	-0.02
Self concept	0.26***	0.19***	0.22***	0.2***
Macedonia				
Science literacy	0.03	0.04	-0.12***	-0.33***
Self efficacy	0.26***	0.2***	0.08***	0.07***
Self concept	0.25***	0.24***	0.18***	0.22***
Mexico				
Science literacy	0.16***	0.17***	-0.11***	-0.16***
Self efficacy	0.24***	0.21***	0.16***	0.12***
Self concept	0.32***	0.26***	0.27***	0.27***
Montenegro				
Science literacy	-0.01	-0.07***	-0.04***	-0.19***
Self efficacy	0.27***	0.25***	0.08***	0.03
Self concept	0.35***	0.3***	0.3***	0.29***
Netherlands				
Science literacy	-0.12***	-0.04	-0.18***	-0.35***

Self efficacy	0.27***	0.19***	0.06**	0.06**
Self concept	0.31***	0.24***	0.14***	0.16***
Norway				
Science literacy	0.11***	0.16***	-0.2***	-0.22***
Self efficacy	0.28***	0.17***	0.13***	0.01
Self concept	0.28***	0.18***	0.2***	0.12***
New Zealand				
Science literacy	0.05*	0.24***	-0.02	-0.29***
Self efficacy	0.26***	0.22***	0.16***	0.06**
Self concept	0.31***	0.25***	0.27***	0.17***
Poland				
Science literacy	-0.04	0.06**	-0.11***	-0.29***
Self efficacy	0.25***	0.21***	0.07***	-0.03
Self concept	0.29***	0.2***	0.22***	0.19***
Portugal				
Science literacy	0.06**	0.16***	-0.09***	-0.3***
Self efficacy	0.27***	0.24***	0.15***	0.07***
Self concept	0.33***	0.24***	0.26***	0.2***
Qatar				
Science literacy	-0.07***	-0.03**	-0.07***	-0.27***
Self efficacy	0.31***	0.3***	0.27***	0.21***
Self concept	0.44***	0.39***	0.42***	0.36***
Romania				
Science literacy	-0.06	0.07***	-0.06**	-0.29***
Self efficacy	0.22***	0.21***	0.15***	0.08***
Self concept	0.32***	0.3***	0.28***	0.27***
Russian Federation				
Science literacy	-0.01	0.02	-0.08***	-0.24***
Self efficacy	0.23***	0.21***	0.1***	0.07***
Self concept	0.29***	0.23***	0.23***	0.26***
Serbia				
Science literacy	-0.12***	0.02	-0.23***	-0.35***
Self efficacy	0.26***	0.23***	0.06**	0.03
Self concept	0.3***	0.23***	0.26***	0.22***
Slovakia				
Science literacy	0.04	0.1*	-0.23***	-0.25***
Self efficacy	0.25***	0.22***	0.06**	0.06**
Self concept	0.25***	0.15***	0.14***	0.13***
Slovenia				
Science literacy	-0.09***	0.15***	-0.11***	-0.26***
Self efficacy	0.22***	0.18***	0.08***	0.06**
Self concept	0.27***	0.18***	0.25***	0.2***
Sweden				
Science literacy	0.09***	0.26***	-0.02	-0.19***
Self efficacy	0.29***	0.21***	0.2***	0.11***

Self concept	0.29***	0.21***	0.24***	0.13***
Chinese - Taipei				
Science literacy	0.1***	0.17***	-0.08***	-0.24***
Self efficacy	0.25***	0.21***	0.12***	0.06***
Self concept	0.22***	0.21***	0.18***	0.19***
Thailand				
Science literacy	0.12***	0.17***	-0.04	-0.06**
Self efficacy	0.33***	0.34***	0.26***	0.25***
Self concept	0.3***	0.32***	0.34***	0.35***
Tunisia				
Science literacy	-0.04	-0.08***	-0.09***	-0.23***
Self efficacy	0.19***	0.23***	0.12***	0.09***
Self concept	0.26***	0.27***	0.23***	0.22***
Turkey				
Science literacy	-0.01	0.22***	0	-0.17***
Self efficacy	0.27***	0.19***	0.18***	0.11***
Self concept	0.34***	0.22***	0.23***	0.24***
Uruguay				
Science literacy	-0.04	-0.03	-0.08***	-0.22***
Self efficacy	0.22***	0.18***	0.12***	0.05
Self concept	0.3***	0.2***	0.26***	0.22***
United States				
Science literacy	0.01	0.13***	-0.09***	-0.31***
Self efficacy	0.22***	0.19***	0.16***	0.1***
Self concept	0.27***	0.25***	0.22***	0.19***

*p < .05. **p < .01. ***p < .001.

In Table D4 correlation coefficients between the various scaled variables of classroom environment (i.e., focus on application; hands-on activities; interactions; and investigations) and both science literacy and self beliefs concerning science are presented. The lowest correlation values and the highest number of both negative and non-significance values were observed when the various classroom environment scales were correlated with science literacy. It seems that the lower scientific literacy is associated with a greater instance of these classroom environment variables. Additionally, the correlation coefficients generally became larger as one moves across the row from the focus on applications scale to the investigations one. Almost without exception, science literacy correlated strongest with investigations ranging from r = -0.06 to r = -0.35 with a slightly negative skew.

Science self-efficacy demonstrated the inverse relationship to science literacy across nations in PISA2006 with the correlations being highest for applications and generally declining across the row (i.e., r = 0.25, 0.22, 0.12 and 0.07 respectively). It is also of note that only six (of 228) correlations were found to be negative and all of these were within the investigations column. Thus, unlike what was observed with scientific literacy, science self-efficacy is associated with a greater instance of these classroom environment variables Finally, science self-concept showed the highest and most consistent correlations with all of the scaled variables of classroom environment demonstrating similar means of r = 0.30 for focus on application; r = 0.24 for hands-on activities; r = 0.23 for interactions; and r = 0.21 for investigations. The range of correlations for self-concept moved from a low of r = 0.11 in investigations to a high of r = 0.44 in investigations and focus on applications.

Discussion

Exploring how differing classroom environments are related to higher levels of science self-efficacy, science self-concept and science achievement are of interest for both researchers and educators. The conceptual change literature (Duit & Treagust, 2003; Pintrich, Marx, & Boyle, 1993; Tyson et al., 1996) clearly argues that scientific literacy requires instructional approaches that are multi-perspective (i.e., how the student views the topic, views their own knowledge and the presence of necessary social/affective conditions), yet simple enough to be easily adapted to instructional routines. It is only through environments such as these that students can achieve the level of scientific literacy required to meet the demands of the future (Duit & Treagust, 2003).

Science Self-beliefs, Science Achievement and Classroom Environments. In Table D4 correlation coefficients between the science classroom learning environments measured in PISA 2006 (i.e., focus on application; hands-on activities; interactions; and, investigations) in columns and science literacy, science self-efficacy and science self-concept in rows are presented. The overall finding of these correlations indicate lowest, and largest number of negative and non-significant values recorded for science literacy (r = -0.06 to r = -0.35) and a general increase across the row from focus on applications scale to the investigations scale. However, because these activities were not ordered in any way by to PISA, this observation across columns with science literacy is made for comparative reasons only. Science self-efficacy demonstrated the inverse relationship to science literacy being highest for applications and generally declining across the row (i.e., r = 0.25, 0.22, 0.12 and 0.07 respectively). Science self-concept showed the highest and most consistent correlations with all of the scaled variables of classroom environment (r = 0.30, 0.24, 0.23 and 0.21).

Those classroom environments which correlate positively and moderately with science self-efficacy and science self-concept correlate negatively with science achievement in PISA. This finding is problematic for the constructivist classroom and efforts to increase scientific literacy. Bloom (1976) theorized that how students felt towards what they were studying, their school environment and their concept of self were potentially adjustable variables that could influence approaches in educating adolescents. The conceptual change model in science education describes learning as an interaction between students' experience and their current understanding of ideas (Pintrich et al., 1993). In a general sense, conceptual change involves building pathways from students' pre-instructional conceptions to the science concepts to be learned and is symbolized by constructivist teaching (Duit, 2003). Constructivism believes that learning about science and doing science is more important than learning scientific knowledge (Hodson, 2006), and constructivist teachers use classroom environments in which learners become actively involved through manipulation of materials and social interaction (Schunk, 2000).

PISA 2006 has sought to reflect this idea of social constructivism by measuring students' abilities to understand and apply science in their assessment instead of simply assessing science content as reflected in more traditional school curriculum. New to 2006, PISA added the organization of school science teaching to their student level questionnaire by asking students how often they were exposed to classroom learning situations that included the focus on applications or models used in teaching, the use of hands-on activities in teaching, if science teaching included peer or teacher interactions and if science teaching included student investigations.

In Table D4 correlation coefficients between science self-concept, science self-efficacy and science literacy and the answers to these classroom environment questions for all countries in the study are presented. When these various classroom environment scales were correlated with science literacy findings are low to moderate and negative across most nations indicating that greater occurrence of these types of classroom environments do not associate with greater science literacy in PISA. Additionally, the correlation coefficients generally became more negative across the row from focus on applications scale to investigations. Almost without exception, science literacy correlated strongest with investigations ranging from r = -0.06 to r = -0.35 with a slightly negative skew. Although there is nothing in the literature uncovered to connect classroom environments that potentially foster non-traditional science instruction to greater achievement on standardized measures, this result is surprising in that it was unexpected and in opposition to the findings for science self-efficacy and science self-concept.

It was hypothesized that exposure to classroom environments that included more constructivist elements would associate positively with science literacy. However, overall the association between these classroom environments as measured through the student questionnaire and science literacy was not positive. This result could be related more to the PISA definition of scientific literacy than a negative association between these measured classroom environments and science achievement. These student questions on classroom environment may be gathering information on science instruction that is designed for local or national curriculum. This data might not be relevant to what PISA is trying to assess with their survey. On reflection, this is not unexpected as PISA was deliberate in not linking their assessment to local curriculum.

One of the criticisms around the conceptual change model for learning science concepts is that it fails to consider that affective measures are linked to content within the learning environment (Duit & Treagust, 2003). If conceptual change approaches towards science education are more effective than traditional ones (and research has shown that conceptual change teaching usually is superior to the more traditional means (Duit & Treagust, 2003)) their efficacy must be linked to classroom practices that support such change.

Perhaps more interesting here are the results of the correlations between classroom environments and science self-beliefs. It was anticipated in this section of the analysis that evidence could merge ideas of conceptual change and theories on the significance of affective factors. The classroom environments as measured in PISA were chosen because they represented characteristics in teaching that implied – albeit indirectly – teachers as reflective and non-transmissive practitioners and students as active, cooperative and self-reflective learners (Duit & Treagust, 2003).

There is a model that proposes if adolescents enter middle or junior high-school with positive feelings towards science, and experience success during their initial courses in science, it is likely that they will elect to take and be more successful in subsequent science courses in high-school and post-secondary studies (Simpson & Oliver, 1990). This in turn leads to a positive commitment to science that influences lifelong interest and learning in science which by definition translates into increased scientific literacy.

A purpose of this exploration was to collect data on the importance of examining science self-beliefs and classroom environments as a facilitator of conceptual change. Science self-efficacy (an individual's beliefs about their performance in a particular domain (Bandura, 1977)) and science self-concept (an individual's representation of all of his or her self-knowledge (Pajares & Schunk, 2003)) were selected because they are measured by PISA and because they represent an individual's beliefs about their ability to perform a science related tasks. For the classroom environment variables, it was anticipated that strong and positive correlations between these and self-belief in science would emerge from the data. Indeed, there is literature that claims teachers who ignore these social and affective measures of personal and group learning may limit conceptual change (Duit & Treagust, 2003).

From the analysis (see Table D4) science self-efficacy demonstrated an inverse relationship to science literacy across nations in PISA 2006 with the overall average correlations being positive and highest for applications and generally declining across the row (i.e., focus on application = 0.25, hands-on activities = 0.22, peer or teacher interactions = 0.12 and student investigations = 0.07). Science self-concept showed the highest and most consistent correlations with all of the scaled variables of classroom environment demonstrating similar means of r = 0.30 for focus on application; r = 0.24 for hands-on activities; r = 0.23 for interactions; and r = 0.21 for investigations.

The findings for science self-efficacy and a positive yet weak correlation with constructivist classroom environments is supported in the literature. Self-efficacy has the potential to either hinder engagement and

subsequent conceptual change with these interactive classrooms as it offers overconfidence with a student's personal beliefs in science or to promote conceptual change by offering students confidence in their ability to change their ideas (Pintrich et al., 1993). The weak correlations lend support to the potential positive and negative relation between self-efficacy and conceptual change as indexed by student questionnaire depending on the nature of the student and the learning environment. However, more variance between countries across the correlations would lend more support to these ideas as would more details by PISA on classroom instructional practices.

The generally higher and more consistent findings for science self-concept with classrooms that appear to be more constructivist and interactive is interesting and potentially promising for nurturing these self-beliefs in students. Because self-concept is a self-descriptive judgment that included how one feels about themselves (in this case as a science student) (Pajares & Schunk, 2002), early science success and associated positive beliefs could be translated into more science literacy, success and course work. Because self-concept includes a student's feelings of self-worth (Bong & Clark, 1999), these classroom environments which appear to be more interactive may offer more opportunity for students to receive ongoing and frequent feedback from peers and teachers and better link their perceived competence and attributes to the classroom norm. In this way, students' beliefs about themselves as learners and the role they play in the classroom learning community can foster conceptual change and scientific literacy.

The multidimensional interpretive framework for conceptual change (see Duit & Treagust, 2003; Tyson et al., 1996) consists of three elements. The ontological one addresses student perceptions of the topic, the epistemological one examines how the student views their own knowledge, and the social/affective view examines what conditions are required for conceptual change. The findings here lend support for providing classroom environments which enrich students' epistemological view of their own learning (both science self-efficacy and science self-concept) as well as their affect by offering supportive and shared opportunities to make personal judgments about theories and conceptions they might have (Tyson et al., 1996). These interactive classrooms can offer the opportunity students need to experience the initial dissatisfaction with their current understanding of the science conception under study. Then receive the opportunity and support required to learn the new concept, see this concept applied in a variety of instances and be offered the opportunity to apply it to new investigations on their own or with peers. In this way both individual beliefs and classroom situations can interact to influence the conceptual change process (Pintrich et al., 1993).

PISA could aid this research agenda by providing more information from the classroom level on what instructional practices were preferred by the teachers and any efforts made to uncover students' ontological view of the topic based upon prior learning and background experiences. In efforts to increase the scientific literacy of students from wide ranging background, the third element of this multidimensional interpretive framework (i.e., the ontological perspective) can be influenced by recognizing students' prior learning and background experiences and potentially modifying them both in and out of the classroom. As can be seen in the next section, cultural and social capital account for sizable variance for scientific literacy and interventions to improve these can both increase achievement and help students to think about science concepts within a more 'scientific' paradigm.

Recommendations. The primary recommendation here is to conduct primary research on conceptual change and attitudinal variables as the classroom level, or potentially adapt measures such as PISA to better capture these environments. Simpson and Oliver (1990) observe that science instruction is not producing students with positive feelings towards science. The theoretical multi-perspective conceptual change approach, as outlined by Duit and Treagust (2003), requires the views of teaching and learning from normal classrooms with data gathered from both normal teachers and normal students. Pintrich et al. (1993) further commented that a research program which truly captures conceptual change and the nature and function of motivations and classroom contextual factors is needed. We have discovered that the rather contrived special arrangements that have been created to conduct conceptual change do not translate into real classrooms (Pintrich et al., 1993) and a better understanding of these real classrooms is warranted.

Duit and Treagust (2003) cite recent developmental projects in school science instruction that share the following: (1) helping educators to rethink how science is represented in curriculum; (2) enlarging the teaching repertoire for instruction and learning; (3) promoting strategies that increase student interest and engagement; and (4) establishing constructivist principles. This study examined the relationship between attitude variables and classroom conditions that were believed to affect science literacy as well as how student background

variables such as SES and immigrant status predicted science achievement. Additionally, some suggestions for educators have also come out of this study which offer potential approaches to improving scientific literacy in general and specifically to help immigrant students succeed in a new educational system.

Appendix E: Histograms of All Achievement Domains in PISA 2006 for Multilevel Models

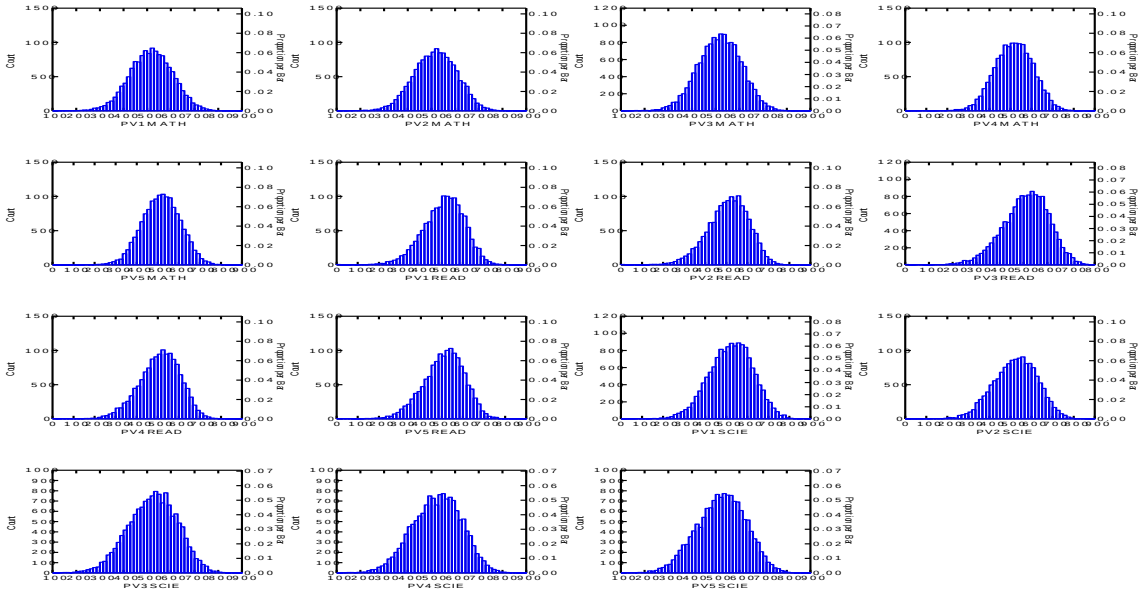

Figure E1. Histograms for the five plausible values for math, reading, and science literacy scores for Australia.

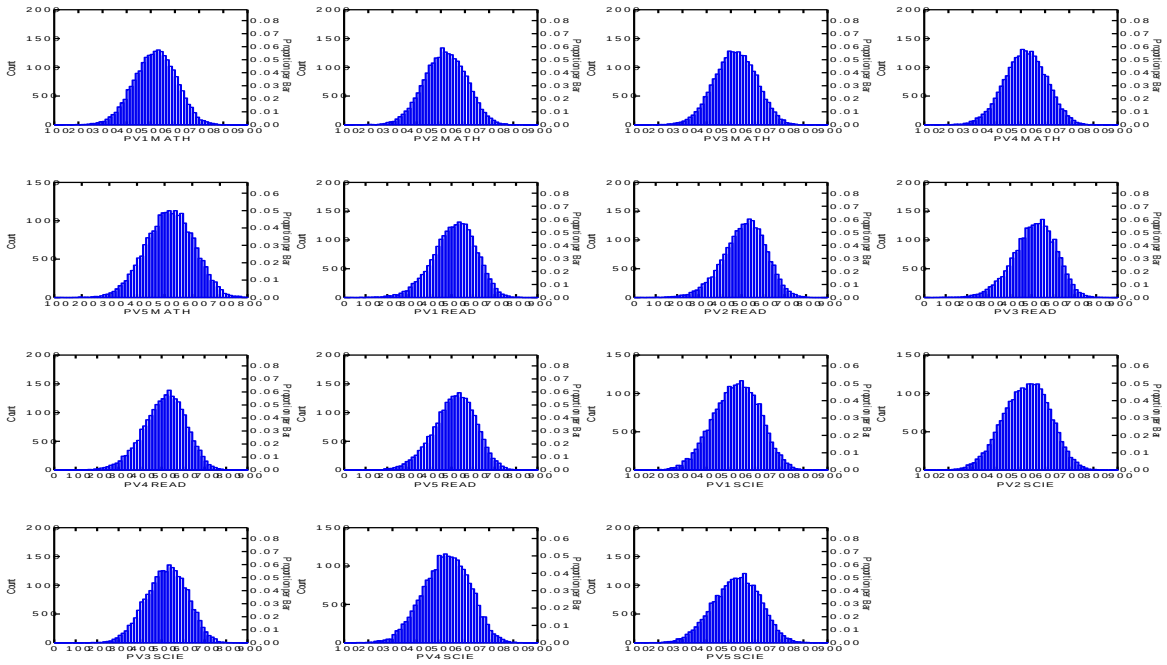

Figure E2. Histograms for the five plausible values for math, reading, and science literacy scores for Canada.

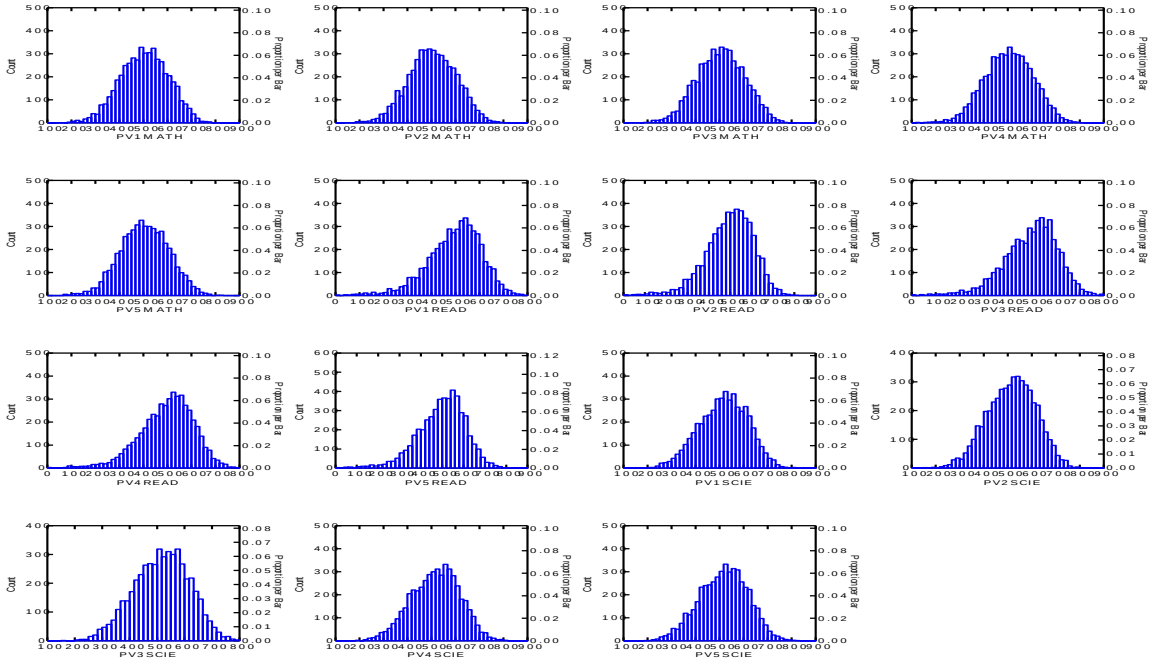

Figure E3. Histograms for the five plausible values for math, reading, and science literacy scores for Germany.

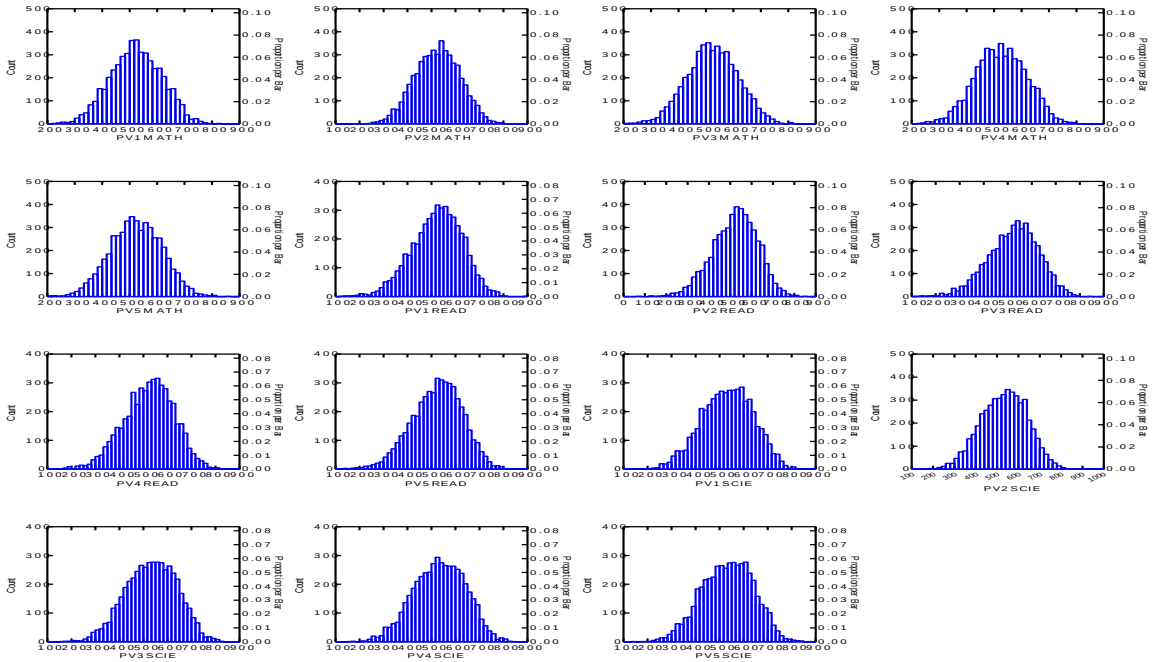

Figure E4. Histograms for the five plausible values for math, reading, and science literacy scores for New Zealand.

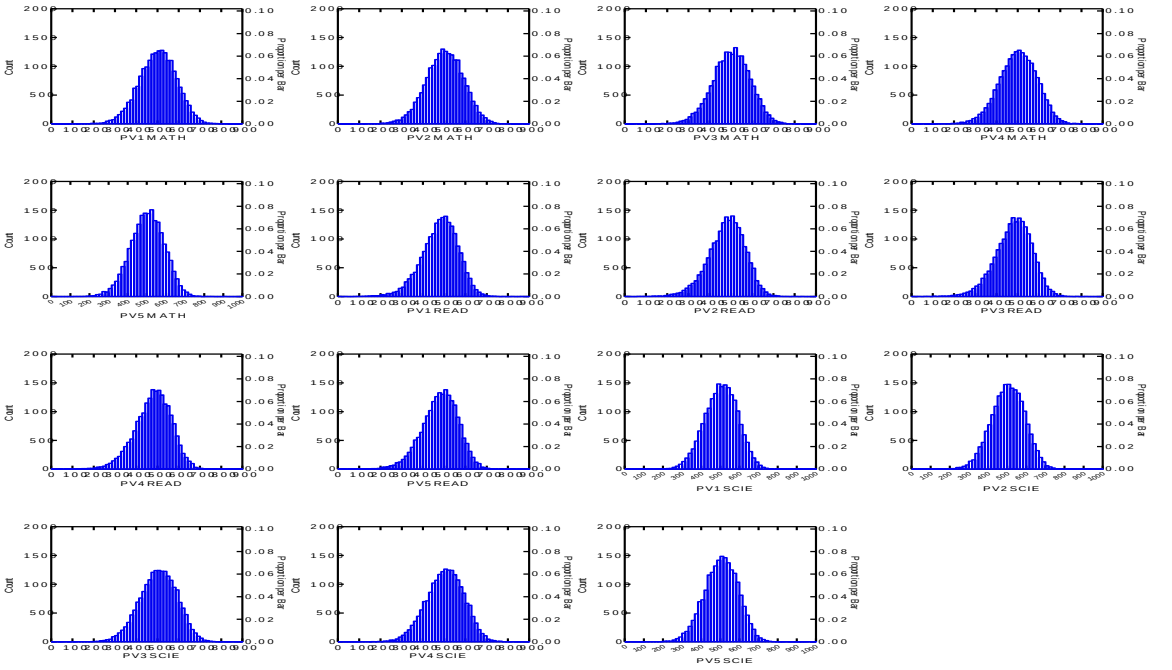

Figure E5. Histograms for the five plausible values for math, reading, and science literacy scores for Spain.

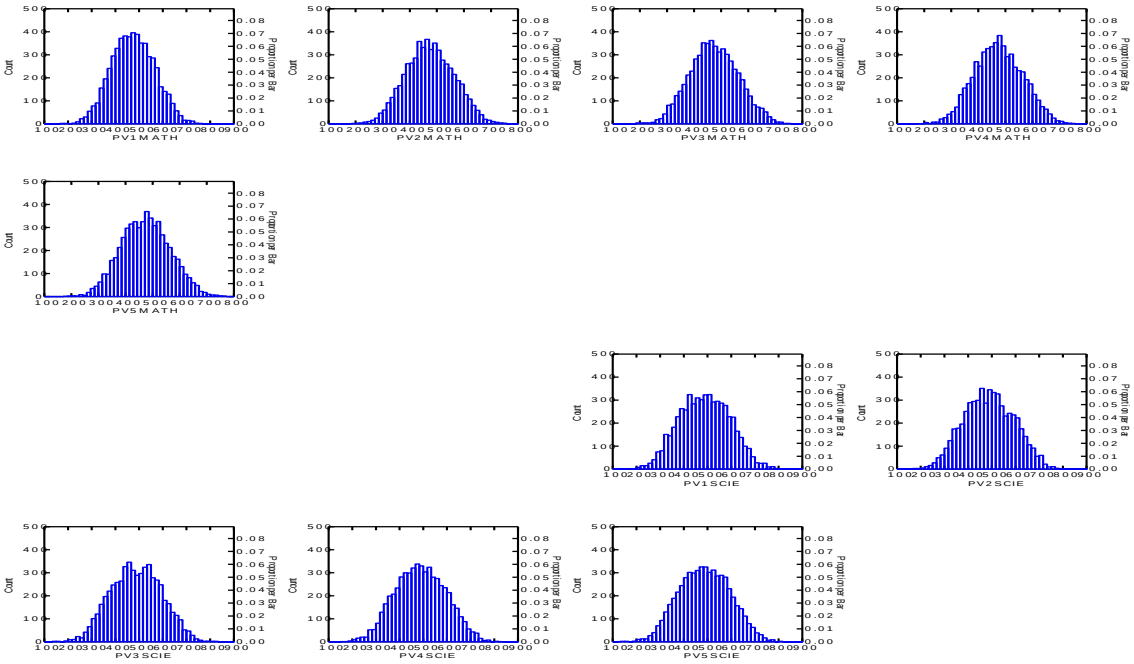

Figure E6. Histograms for the five plausible values for math, reading, and science literacy scores for the United States.

Appendix F: Scatterplot Matricies for Select Student-Level Variables in PISA 2006 for Austalia

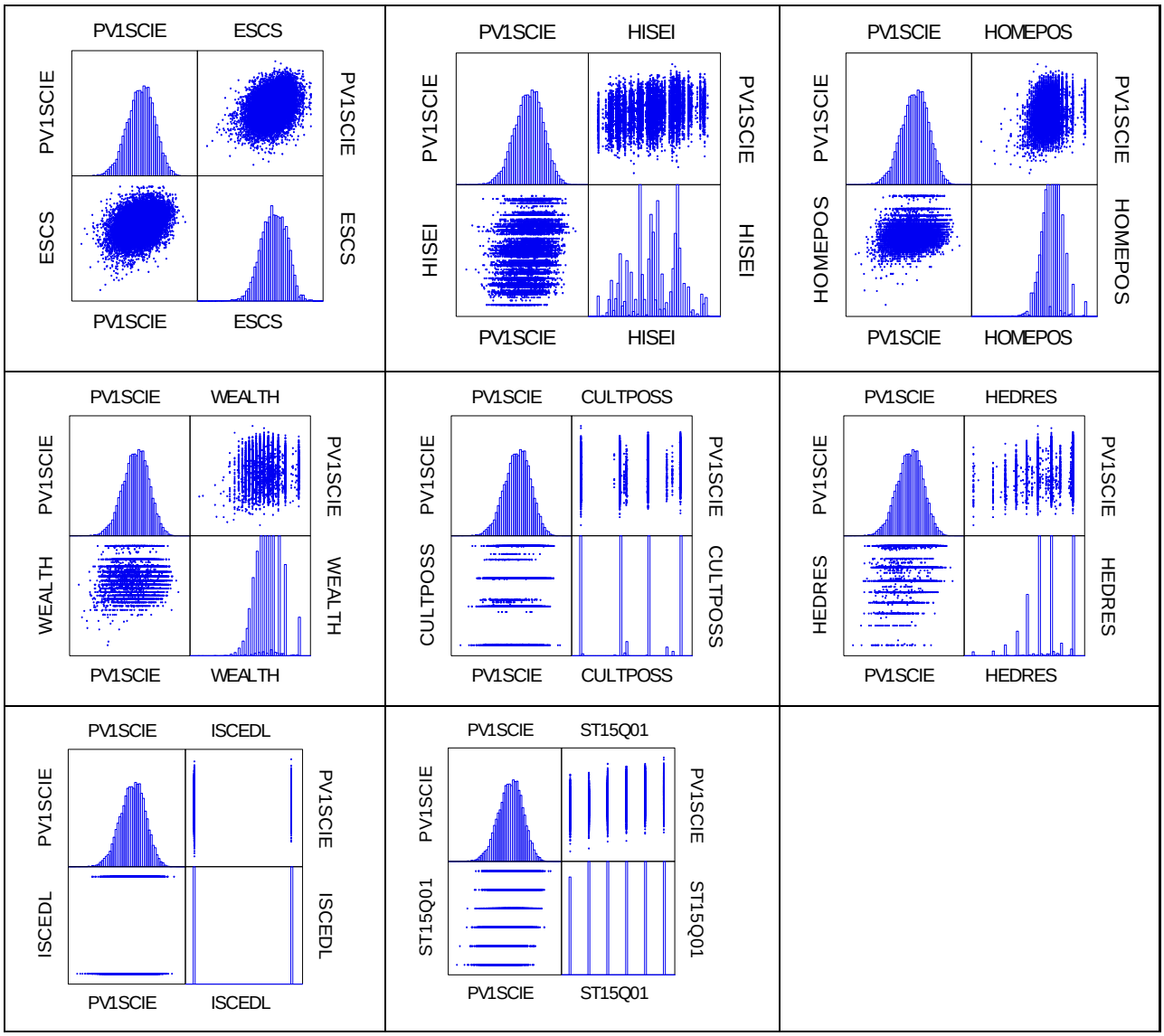

Figure F1. ESCS, HISEI, HOMEPOS, WEALTH, CULTPOS, HEDRES, ISCEDL, ST15Q01.

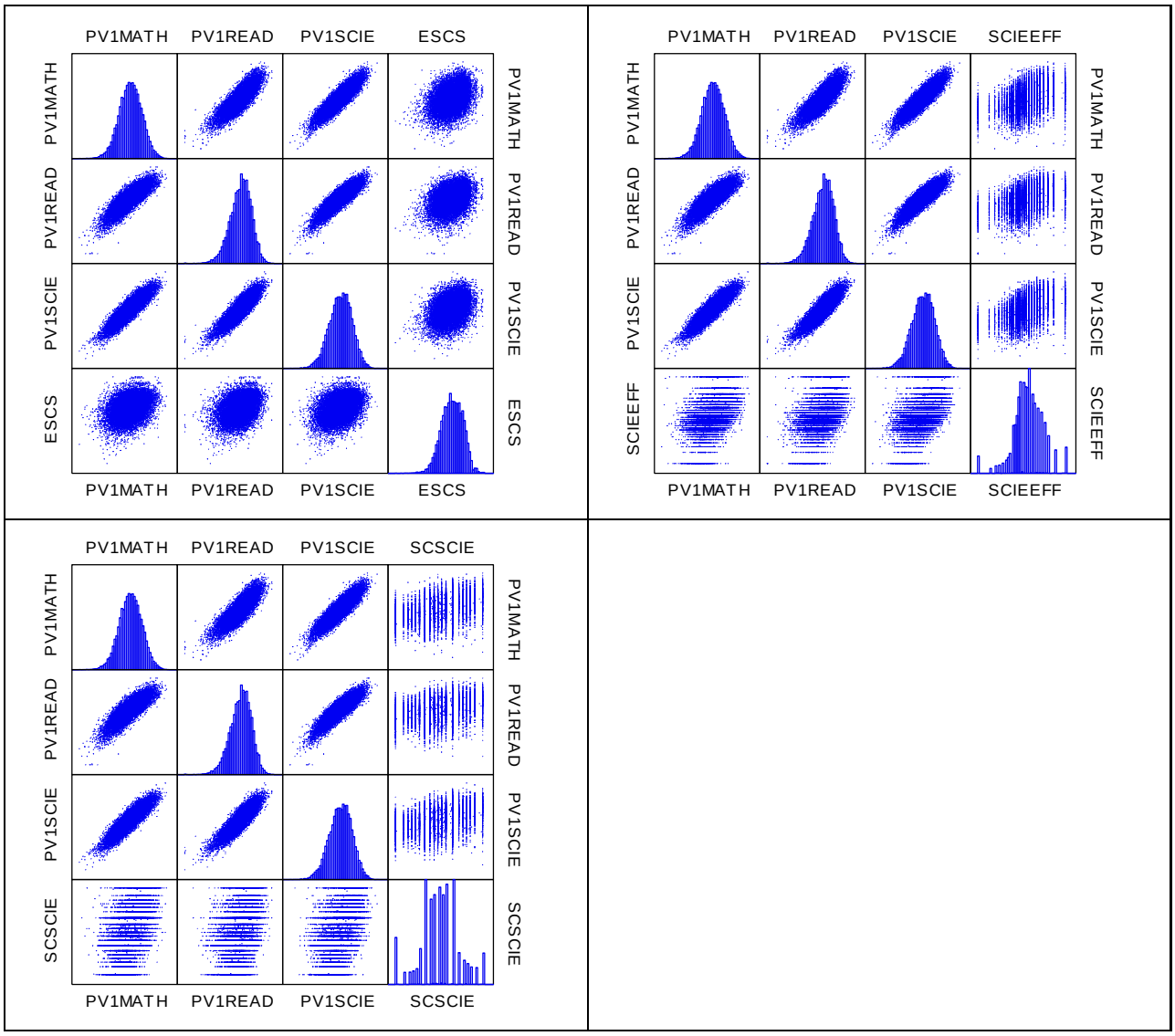

Figure F2. Scatterplot matrices for PV1 science, mathematics, reading, and ESCS, science self-efficacy and science self-concept for Australia.

Appendix G: Residual Plots for Regression Equations from PISA 2006 for Australia

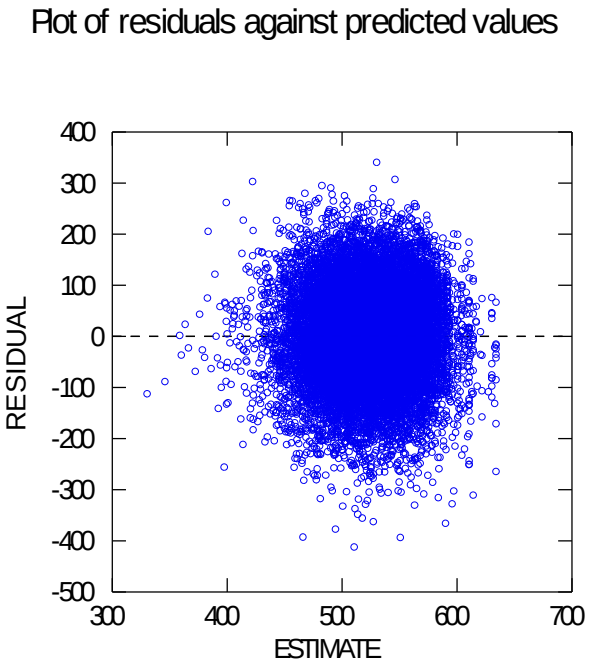

Figure G1. Cultural capital.

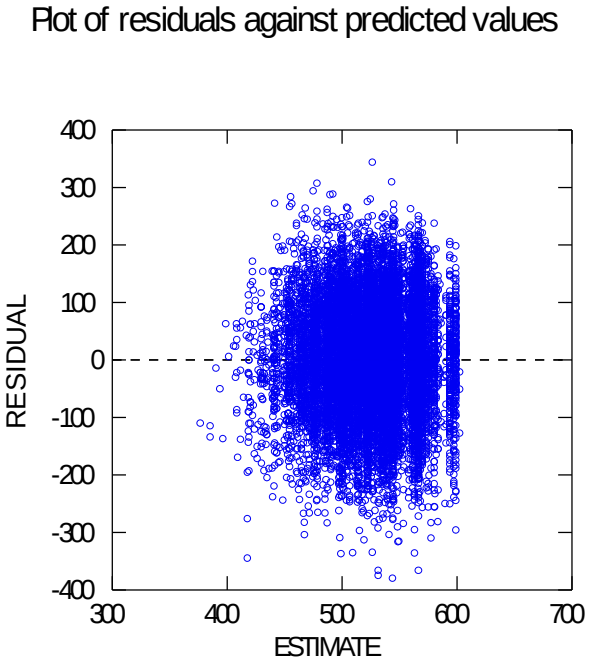

Figure G2. Social capital.

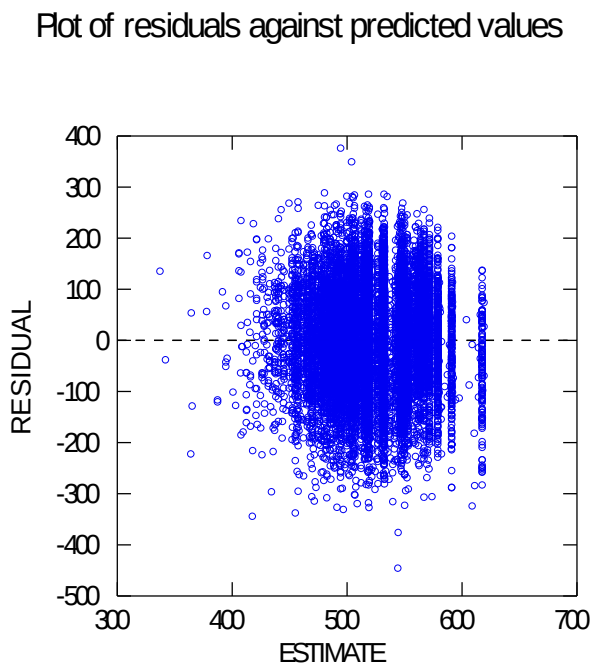

Figure G3. Economic capital.

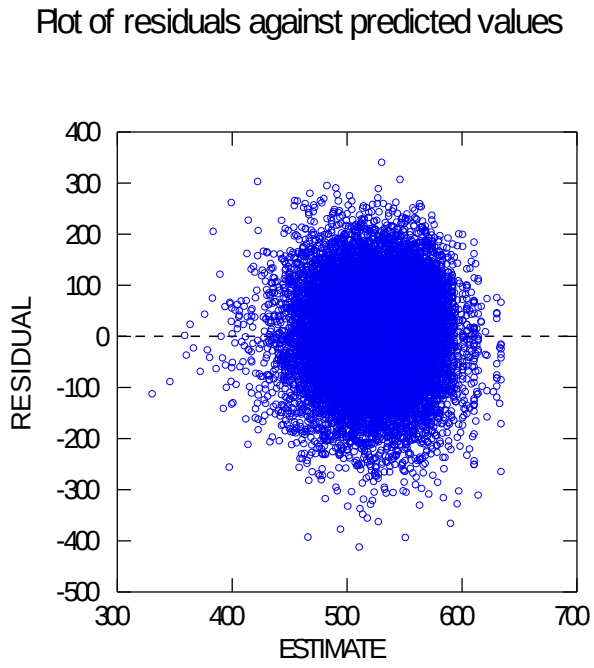

Figure G4. ESCS.

Appendix H: Null Models

Table H1

Null Models for Science Literacy Achievement

a. Australia

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
General Math Ability (Intercept, γ_{00})	524.63	2.85	183.85	335	0.000
	Variance Component	*SD*	χ^2	*df*	*p*
Random Effects					
School -Level (*u*)	1894.47	43.52	3470.25	335	0.000
Student -Level (*r*)	8239.64	90.77			

Variance attributable to schools = $\frac{1894.47}{1894.47 + 8239.64} = 0.19$

b. Canada

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
General Math Ability (Intercept, γ_{00})	531.90	2.35	226.61	895	0.000
	Variance Component	*SD*	χ^2	*df*	*p*
Random Effects					
School -Level (*u*)	1839.66	42.89	6253.46	895	0.000
Student -Level (*r*)	7187.01	84.78			

Variance attributable to schools = $\frac{1839.66}{1839.66 + 7187.01} = 0.20$

c. Germany

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		

Fixed Effects					
General Math Ability (Intercept, γ_{00})	507.17	5.51	92.08	225	0.000
	Variance Component	*SD*	χ^2	*df*	*p*
Random Effects					
School -Level (*u*)	5997.30	77.44	6206.99	225	0.000
Student -Level (*r*)	4530.86	67.31			

Variance attributable to schools = $\frac{5997.30}{5997.30 + 4530.86} = 0.57$

d. New Zealand

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
General Math Ability (Intercept, γ_{00})	525.86	4.01	131.11	169	0.000
	Variance Component	*SD*	χ^2	*df*	*p*
Random Effects					
School -Level (*u*)	2040.43	45.17	1110.68	169	0.000
Student -Level (*r*)	9654.59	98.26			

Variance attributable to schools = $\frac{2040.43}{2040.43 + 9654.59} = 0.17$

e. Spain

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
General Math Ability (Intercept, γ_{00})	486.64	2.82	172.12	685	0.000
	Variance Component	*SD*	χ^2	*df*	*p*
Random Effects					
School -Level (*u*)	1515.04	38.92	5018.82	685	0.000
Student -Level (*r*)	6717.77	81.96			

Variance attributable to schools = $\frac{1515.04}{1515.04 + 6717.77} = 0.18$

f. United States

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
General Math Ability (Intercept, γ_{00})	489.66	5.28	92.72	165	0.000
	Variance Component	*SD*	χ^2	*df*	*p*
Random Effects					
School -Level (*u*)	2839.57	53.28	2008.53	165	0.000
Student -Level (*r*)	8468.21	92.02			

Variance attributable to schools = $\frac{2839.57}{2839.57 + 8468.21} = 0.23$

Table H2

Null Models for Mathematics Literacy Achievement

a. Australia

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Science Ability (Intercept, γ_{00})	517.83	2.74	188.88	355	0.000
	Variance Component	*SD*	χ^2	*df*	*p*
Random Effects					
School -Level (*u*)	1774.19	42.12	4306.06	355	0.000
Student -Level (*r*)	6062.37	77.86			

Variance attributable to schools = $\frac{1774.19}{1774.19 + 6062.37} = 0.23$

b. Canada

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Science Ability (Intercept, γ_{00})	524.60	2.12	247.22	895	0.000
	Variance Component	*SD*	χ^2	*df*	*p*
Random Effects					
School -Level (*u*)	1649.54	40.61	6726.41	895	0.000
Student -Level (*r*)	5865.34	76.59			

Variance attributable to schools = $\frac{1649.54}{1649.54 + 5865.34} = 0.22$

c. Germany

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Science Ability (Intercept, γ_{00})	495.64	5.63	88.05	225	0.000
	Variance Component	*SD*	χ^2	*df*	*p*
Random Effects					
School -Level (*u*)	6279.83	79.24	7452.23	225	0.000
Student -Level (*r*)	3989.84	63.16			

Variance attributable to schools = $\frac{6279.83}{6279.83 + 3989.84} = 0.61$

d. New Zealand

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Science Ability (Intercept, γ_{00})	517.93	3.44	150.46	169	0.000
	Variance Component	*SD*	χ^2	*df*	*p*
Random Effects					

School -Level (*u*)	1468.55	38.32	1071.68	169	0.000
Student -Level (*r*)	7355.99	85.77			

Variance attributable to schools = $\frac{1468.55}{1468.55 + 7355.99} = 0.16$

e. Spain

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Science Ability (Intercept, γ_{00})	478.43	2.70	177.03	685	0.000
	Variance Component	*SD*	χ^2	*df*	*p*
Random Effects					
School -Level (*u*)	1472.31	38.37	5121.15	685	0.000
Student -Level (*r*)	6449.09	80.30			

Variance attributable to schools = $\frac{1472.31}{1472.31 + 6449.09} = 0.19$

f. United States

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Science Ability (Intercept, γ_{00})	473.85	4.79	98.84	165	0.000
	Variance Component	*SD*	χ^2	*df*	*p*
Random Effects					
School -Level (*u*)	2365.46	48.64	2452.70	165	0.000
Student -Level (*r*)	5722.48	75.65			

Variance attributable to schools = $\frac{2365.46}{2365.46 + 5722.48} = 0.29$

Table H3

Null Models for Reading Literacy Achievement

a. Australia

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Reading literacy (Intercept, γ_{00})	510.99	2.68	190.57	355	0.000
	Variance Component	*SD*	χ^2	*df*	*p*
Random Effects					
School -Level (*u*)	1853.25	43.05	3902.91	355	0.000
Student -Level (*r*)	7036.16	83.88			

Variance attributable to schools = $\frac{1853.25}{1853.25 + 7036.16} = 0.23$

b. Canada

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Reading literacy (Intercept, γ_{00})	524.58	2.58	203.35	895	0.000
	Variance Component	*SD*	χ^2	*df*	*p*
Random Effects					
School -Level (*u*)	2363.96	46.62	7782.34	895	0.000
Student -Level (*r*)	7113.66	84.34			

Variance attributable to schools = $\frac{2363.96}{2363.96 + 7113.66} = 0.25$

c. Germany

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Reading literacy (Intercept, γ_{00})	481.75	7.10	67.85	225	0.000
	Variance Component	*SD*	χ^2	*df*	*p*
Random Effects					
School -Level (*u*)	9984.53	99.92	8594.17	225	0.000
Student -Level (*r*)	4688.65	68.47			

Variance attributable to schools = $\frac{9984.3}{9984.53 + 4688.65} = 0.68$

d. New Zealand

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Reading literacy (Intercept, γ_{00})	516.64	4.20	122.96	169	0.000
	Variance Component	*SD*	χ^2	*df*	*p*
Random Effects					
School -Level (*u*)	2253.49	47.47	1232.91	169	0.000
Student -Level (*r*)	9089.32	95.34			

Variance attributable to schools = $\frac{2253.49}{2253.49 + 9089.32} = 0.20$

e. Spain

Variables	Parameters Estimate			*df*	*p*
	Coefficient	*SE*	*t*		
Fixed Effects					
Reading literacy (Intercept, γ_{00})	459.43	2.91	157.43	685	0.000
	Variance Component	*SD*	χ^2	*df*	*p*
Random Effects					
School -Level (*u*)	1679.60	40.98	5846.53	685	0.000
Student -Level (*r*)	6249.30	79.05			

Variance attributable to schools = $\frac{1679.60}{1679.60 + 6249.30} = 0.21$

f. No PV's in *Reading literacy* were reported for the United States in PISA 2006

Appendix I: Final Hierarchical Models for Literacy Domains Across All Selected Nations

Table I1

Final Models for Science Literacy Across All Selected Nations

Australia

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{IMMIGRANT}) + \beta_{2j}(\text{SelfEff}) + \beta_{3j}(\text{SelfCon}) + \beta_{4j}(\text{ESCS}) + r_{ij}$$
$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + u_{0j}$$
$$\beta_{1j} = \gamma_{10} + \gamma_{11}(\text{PROIMM}) + u_{1j}$$
$$\beta_{2j} = \gamma_{20} + u_{2j}$$
$$\beta_{3j} = \gamma_{30} + \gamma_{31}(\text{SCHESCS}) + u_{3j}$$
$$\beta_{4j} = \gamma_{40} + u_{4j}$$

Canada

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{IMMIGRANT}) + \beta_{2j}(\text{SelfEff}) + \beta_{3j}(\text{SelfCon}) + \beta_{4j}(\text{ESCS}) + r_{ij}$$
$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + u_{0j}$$
$$\beta_{1j} = \gamma_{10} + u_{1j}$$
$$\beta_{2j} = \gamma_{20} + u_{2j}$$
$$\beta_{3j} = \gamma_{30} + u_{3j}$$
$$\beta_{4j} = \gamma_{40} + u_{4j}$$

Germany

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{IMMIGRANT}) + \beta_{2j}(\text{SelfEff}) + \beta_{3j}(\text{SelfCon}) + \beta_{4j}(\text{ESCS}) + r_{ij}$$
$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + u_{0j}$$
$$\beta_{1j} = \gamma_{10}$$
$$\beta_{2j} = \gamma_{20}$$
$$\beta_{3j} = \gamma_{30}$$
$$\beta_{4j} = \gamma_{40}$$

New Zealand

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{IMMIGRANT}) + \beta_{2j}(\text{SelfEff}) + \beta_{3j}(\text{SelfCon}) + \beta_{4j}(\text{ESCS}) + r_{ij}$$
$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + u_{0j}$$
$$\beta_{1j} = \gamma_{10}$$
$$\beta_{2j} = \gamma_{20} + u_{2j}$$
$$\beta_{3j} = \gamma_{30} + \gamma_{31}(\text{SCHESCS}) + u_{3j}$$
$$\beta_{4j} = \gamma_{40} + \gamma_{41}(\text{SCHESCS}) + \gamma_{41}(\text{PROIMM})$$

Spain

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{IMMIGRANT}) + \beta_{2j}(\text{SelfEff}) + \beta_{3j}(\text{SelfCon}) + \beta_{4j}(\text{ESCS}) + r_{ij}$$
$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + u_{0j}$$
$$\beta_{1j} = \gamma_{10} + u_{1j}$$
$$\beta_{2j} = \gamma_{20} + u_{2j}$$
$$\beta_{3j} = \gamma_{30} + \gamma_{31}(\text{SCHESCS}) + u_{3j}$$
$$\beta_{4j} = \gamma_{40} + u_{4j}$$

United States

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{IMMIGRANT}) + \beta_{2j}(\text{SelfEff}) + \beta_{3j}(\text{SelfCon}) + \beta_{4j}(\text{ESCS}) + r_{ij}$$
$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + u_{0j}$$
$$\beta_{1j} = \gamma_{10} + u_{1j}$$
$$\beta_{2j} = \gamma_{20} + u_{2j}$$
$$\beta_{3j} = \gamma_{30} + \gamma_{31}(\text{SCHESCS})$$
$$\beta_{4j} = \gamma_{40}$$

Table I2

Final Models for Mathematics Literacy Across All Selected Nations

Australia

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{SelfEff}) + \beta_{2j}(\text{SelfCon}) + \beta_{3j}(\text{ESCS}) + r_{ij}$$
$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + u_{0j}$$
$$\beta_{1j} = \gamma_{10} + u_{1j}$$
$$\beta_{2j} = \gamma_{20} + \gamma_{21}(\text{SCHESCS}) + u_{2j}$$
$$\beta_{3j} = \gamma_{30}$$

Canada

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{IMMIGRANT}) + \beta_{2j}(\text{SelfEff}) + \beta_{3j}(\text{SelfCon}) + \beta_{4j}(\text{ESCS}) + r_{ij}$$
$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + u_{0j}$$
$$\beta_{1j} = \gamma_{10} + u_{1j}$$
$$\beta_{2j} = \gamma_{20} + u_{2j}$$
$$\beta_{3j} = \gamma_{30} + u_{3j}$$
$$\beta_{4j} = \gamma_{40} + u_{4j}$$

Germany

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{IMMIGRANT}) + \beta_{2j}(\text{SelfEff}) + \beta_{3j}(\text{SelfCon}) + \beta_{4j}(\text{ESCS}) + r_{ij}$$
$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + u_{0j}$$
$$\beta_{1j} = \gamma_{10}$$
$$\beta_{2j} = \gamma_{20}$$
$$\beta_{3j} = \gamma_{30}$$
$$\beta_{4j} = \gamma_{40}$$

New Zealand

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{SelfEff}) + \beta_{2j}(\text{SelfCon}) + \beta_{3j}(\text{ESCS}) + r_{ij}$$
$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + \gamma_{02}(\text{PROIMM}) + u_{0j}$$
$$\beta_{1j} = \gamma_{10}$$
$$\beta_{2j} = \gamma_{20} + \gamma_{21}(\text{SCHESCS})$$
$$\beta_{3j} = \gamma_{30} + \gamma_{31}(\text{PROIMM})$$

Spain

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{IMMIGRANT}) + \beta_{2j}(\text{SelfEff}) + \beta_{3j}(\text{SelfCon}) + \beta_{4j}(\text{ESCS}) + r_{ij}$$
$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + u_{0j}$$
$$\beta_{1j} = \gamma_{10} + u_{1j}$$
$$\beta_{2j} = \gamma_{20} + u_{2j}$$
$$\beta_{3j} = \gamma_{30} + \gamma_{31}(\text{SCHESCS}) + u_{3j}$$

$\beta_{4j} = \gamma_{40} + u_{4j}$

United States

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{SelfEff}) + \beta_{2j}(\text{SelfCon}) + \beta_{3j}(\text{ESCS}) + r_{ij}$
$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + u_{0j}$
$\beta_{1j} = \gamma_{10} + \gamma_{11}(\text{SCHESCS})$
$\beta_{2j} = \gamma_{20}$
$\beta_{3j} = \gamma_{30}$

Table I3

Final Models for Reading Literacy Across All Selected Nations

Australia

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{IMMIGRANT}) + \beta_{2j}(\text{SelfEff}) + \beta_{3j}(\text{SelfCon}) + \beta_{4j}(\text{ESCS}) + r_{ij}$
$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + u_{0j}$
$\beta_{1j} = \gamma_{10} + u_{1j}$
$\beta_{2j} = \gamma_{20} + u_{2j}$
$\beta_{3j} = \gamma_{30} + u_{3j}$
$\beta_{4j} = \gamma_{40} + u_{4j}$

Canada

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{IMMIGRANT}) + \beta_{2j}(\text{SelfEff}) + \beta_{3j}(\text{SelfCon}) + \beta_{4j}(\text{ESCS}) + r_{ij}$
$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + u_{0j}$
$\beta_{1j} = \gamma_{10} + u_{1j}$
$\beta_{2j} = \gamma_{20} + u_{2j}$
$\beta_{3j} = \gamma_{30} + u_{3j}$
$\beta_{4j} = \gamma_{40} + u_{4j}$

Germany

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{IMMIGRANT}) + \beta_{2j}(\text{SelfEff}) + \beta_{3j}(\text{ESCS}) + r_{ij}$
$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + u_{0j}$
$\beta_{1j} = \gamma_{10}$
$\beta_{2j} = \gamma_{20}$
$\beta_{3j} = \gamma_{30}$

New Zealand

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{SelfEff}) + \beta_{2j}(\text{SelfCon}) + \beta_{3j}(\text{ESCS}) + r_{ij}$
$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + u_{0j}$
$\beta_{1j} = \gamma_{10}$
$\beta_{2j} = \gamma_{20} + u_{2j}$
$\beta_{3j} = \gamma_{30} + \gamma_{31}(\text{PROIMM})$

Spain

$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{IMMIGRANT}) + \beta_{2j}(\text{SelfEff}) + \beta_{3j}(\text{SelfCon}) + \beta_{4j}(\text{ESCS}) + r_{ij}$
$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{SCHESCS}) + u_{0j}$
$\beta_{1j} = \gamma_{10} + u_{1j}$
$\beta_{2j} = \gamma_{20} + u_{2j}$
$\beta_{3j} = \gamma_{30} + u_{3j}$

$\beta_{4j} = \gamma_{40} + u_{4j}$

United States

n/a

Appendix J: Correlations Between Literacy Domains Across All Participating Nations in PISA 2000, 2003 and 2006

Table J1

Correlations Between Literacy Domains for PISA 2000

Country	Reading & Math	Science & Reading	Science & Math
ALB	0.60	0.75	0.74
ARG	0.64	0.77	0.82
AUS	0.82	0.81	0.89
AUT	0.81	0.81	0.89
BEL	0.86	0.88	0.88
BGR	0.63	0.78	0.73
BRA	0.73	0.80	0.81
CAN	0.78	0.80	0.88
CHE	0.62	0.81	0.80
CHL	0.82	0.83	0.87
CZE	0.76	0.83	0.87
DEU	0.76	0.75	0.83
DNK	0.79	0.80	0.85
ESP	0.83	0.86	0.87
FIN	0.75	0.76	0.80
FRA	0.79	0.82	0.87
GBR	0.76	0.82	0.85
GRC	0.69	0.78	0.82
HKG	0.70	0.69	0.67
HUN	0.84	0.82	0.90
IDN	0.72	0.72	0.79
IRL	0.73	0.79	0.86
ISL	0.77	0.78	0.85
ISR	0.80	0.76	0.82
ITA	0.76	0.72	0.78
JPN	0.78	0.83	0.89
KOR	0.82	0.83	0.89
LIE	0.79	0.82	0.83
LUX	0.82	0.87	0.90
LVA	0.86	0.86	0.92
MEX	0.79	0.80	0.87
MKD	0.57	0.77	0.69
NLD	0.83	0.84	0.85
NOR	0.79	0.85	0.88
NZL	0.73	0.83	0.83
PER	0.69	0.77	0.81
POL	0.71	0.79	0.84
PRT	0.77	0.84	0.87
ROM	0.79	0.83	0.88
RUS	0.75	0.79	0.81
SWE	0.76	0.79	0.80
THA	0.90	0.88	0.91
USA	0.85	0.88	0.91

Table J2

Correlations Between Literacy Domains for PISA 2003

Country	Reading & Math	Science & Reading	Science & Math
AUS	0.75	0.78	0.81
AUT	0.77	0.79	0.84
BEL	0.80	0.81	0.84
BRA	0.6	0.58	0.64
CAN	0.75	0.77	0.80
CHE	0.75	0.76	0.81
CZE	0.76	0.79	0.80
DEU	0.80	0.82	0.86
DNK	0.70	0.71	0.77
ESP	0.68	0.71	0.72
FIN	0.68	0.72	0.76
FRA	0.7	0.78	0.77
GBR	0.8	0.82	0.85
GRC	0.58	0.62	0.63
HKG	0.79	0.78	0.83
HUN	0.71	0.75	0.75
IDN	0.64	0.62	0.64
IRL	0.77	0.79	0.80
ISL	0.73	0.74	0.76
ITA	0.68	0.71	0.74
JPN	0.76	0.80	0.79
KOR	0.74	0.75	0.82
LIE	0.76	0.79	0.82
LUX	0.75	0.79	0.82
LVA	0.68	0.71	0.72
MAC	0.58	0.65	0.66
MEX	0.68	0.63	0.66
NLD	0.84	0.83	0.86
NOR	0.72	0.74	0.78
NZL	0.79	0.80	0.84
POL	0.71	0.72	0.75
PRT	0.71	0.76	0.78
RUS	0.59	0.66	0.66
SVK	0.74	0.74	0.78
SWE	0.73	0.76	0.77
THA	0.64	0.65	0.69
TUN	0.58	0.54	0.61
TUR	0.73	0.77	0.80
URY	0.54	0.57	0.57
USA	0.81	0.82	0.83
BEL	0.80	0.81	0.84
BRA	0.6	0.58	0.65
YUG	0.66	0.69	0.68

Table J3

Correlations Between Literacy Domains for PISA 2006

Country	Reading & Math	Reading & Science	Science & Math
ARG	0.68	0.75	0.76
AUS	0.83	0.88	0.89
AUT	0.78	0.85	0.88
AZE	0.38	0.68	0.63
BEL	0.83	0.88	0.9
BGR	0.77	0.84	0.85
BRA	0.71	0.74	0.8
CAN	0.78	0.84	0.85
CHE	0.82	0.89	0.9
CHL	0.72	0.75	0.85
COL	0.57	0.61	0.68
CZE	0.8	0.86	0.89
DEU	0.81	0.86	0.9
DNK	0.79	0.86	0.89
ESP	0.75	0.8	0.86
EST	0.82	0.85	0.89
FIN	0.74	0.81	0.86
FRA	0.77	0.85	0.89
GBR	0.82	0.87	0.89
GRC	0.69	0.82	0.81
HKG	0.8	0.84	0.9
HRV	0.79	0.86	0.88
HUN	0.8	0.85	0.89
IDN	0.79	0.79	0.81
IRL	0.82	0.86	0.88
ISL	0.8	0.85	0.87
ISR	0.76	0.83	0.84
ITA	0.69	0.76	0.83
JOR	0.73	0.8	0.83
JPN	0.79	0.86	0.86
KGZ	0.66	0.67	0.72
KOR	0.81	0.87	0.88
LIE	0.83	0.9	0.91
LTU	0.76	0.85	0.89
LUX	0.82	0.89	0.89
LVA	0.75	0.82	0.86
MAC	0.69	0.77	0.82
MEX	0.73	0.76	0.82
MNE	0.74	0.87	0.84
NLD	0.85	0.88	0.91
NOR	0.77	0.84	0.87
NZL	0.79	0.88	0.89
POL	0.77	0.84	0.89
PRT	0.8	0.85	0.89
QAT	0.75	0.86	0.8
ROU	0.71	0.8	0.86
RUS	0.64	0.73	0.78
SRB	0.76	0.83	0.85
SVK	0.78	0.84	0.88
SVN	0.76	0.85	0.88

SWE	0.79	0.84	0.89
TAP	0.82	0.87	0.89
THA	0.73	0.8	0.82
TUN	0.65	0.73	0.73
TUR	0.7	0.79	0.85
URY	0.62	0.69	0.74
USA	-	-	0.9