ABSTRACT

Title of Document:	SCHOOL AND INDIVIDUAL FACTORS THAT CONTRIBUTE TO THE ACHIEVEMENT GAP IN COLLEGE ADMISSIONS TESTS IN CHILE
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In Chile, reports and research papers have shown that there is an achievement gap in college admissions tests mostly associated to students' gender, socioeconomic status and type of school attended. This gap represents a barrier for low-income and female students to access higher education, as well as for graduates of public schools. Prior studies have used descriptive analyses and single-level linear regression to study this gap, which do not take into account the nested structure of the data (students nested within schools). This study uses multilevel linear modeling to concurrently estimate the effect of student and school characteristics on individual performance in admissions tests in Chile. The findings revealed that more than half of the variation in college admissions test scores happens at the school level. This variation between schools is mostly explained by school sector (private, subsidized private, and public) and the average school socioeconomic status. At the individual level, the most

influential factor is individual high school GPA. These findings have important implications for policy and practice, as publicly funded universities in Chile rely almost exclusively on test scores to select students and need-based financial aid requires students to score above a minimum threshold. The results of this study suggest that these admission and financial aid policies need to be reconsidered in order to increase opportunity of access to higher education for traditionally excluded students.

SCHOOL AND INDIVIDUAL FACTORS THAT CONTRIBUTE TO THE
ACHIEVEMENT GAP IN COLLEGE ADMISSIONS TESTS IN CHILE

By

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2012

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Dedication

To my mother, Susana Mejías, for her unconditional love and support, and for all the sacrifices she made to give me the best education possible.

I am also grateful from my friends and colleagues Doris Rodés, Lorena López, Danae de Los Ríos, Daniela Matamala, and Dora Altbir. During this journey, even from the distance, these wonderful women have been great mentors, friends, and continuous source of inspiration for my work.

Most importantly, I want to thank my husband, Mauro, for being such a perfect partner to share this experience with. His willingness and patience to listen and discuss higher education topics was inexhaustible and I will be always grateful of his contributions to my academic work. He is also a wonderful father and took care of our son Alonso by his own when I needed to work on my dissertation. My son, Alonso, also contributed to the completion of this study by becoming my main motivation to finish the program so I could spend more time with him.

Finally, I also want to acknowledge that my doctoral program and this study would not have been possible without the financial assistance of four institutions: Universidad de Santiago de Chile, MECESUP, the Fulbright Program, and the Graduate School of the University of Maryland, College Park. I would be always grateful to these institutions for providing me with the financial resources that allowed me to be a full-time student focused exclusively on my program, which was critical for me to successfully complete my doctoral studies.

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Chapter 1: Introduction

In Chile, college admissions tests have long been a main barrier to access to the most selective Chilean universities, especially for low-income and female students, and for graduates of public high schools (Contreras, Corbalán, & Redondo, 2007; CTA-CRUCH, 2004; 2005; Fontaine, 2002; Gil & Grez, 2002; Gil & Ureta, 2003; Le Foulon, 2002; Le Foulon & Beyer, 2002). The national college admission testing model was rehauled in 2003 in an attempt to reduce the test score gender and income-based gap (Koljatic & Silva, 2006; 2010). However, since this revised model was implemented, female and low-income students, and graduates of public high schools still consistently obtain lower scores on admissions test than their respective counterparts (Contreras, Corbalán, & Redondo, 2007; CTA-CRUCH, 2004; 2005).

Because students cannot earn admission to a selective university (DEMRE, 2011) or apply or qualify for state financial aid (MINEDUC, 2011; OECD & The World Bank, 2009) without earning an admissions test score above a certain threshold, the stakes for performing well on the college admissions test are high. Moreover, the Chilean government allocates additional funds to postsecondary institutions to recruit and enroll students who earned high scores on the admissions test. Admission standards coupled with state funding creates a financial disincentive for institutions to educate underrepresented students who systematically score lower on their tests than their more privileged counterparts (Hudson, 1994; OECD & The World Bank, 2009).

The purpose of this study is to identify the main individual characteristics that have an impact on performance in college admissions tests among Chilean high school graduates. Also, this study aims to ascertain the extent to which Chilean high schools

affect students' performance on college admissions tests. Consequently, the research questions guiding this study are as follows:

1. To what extent does the students' performance on college admissions tests vary across Chilean high schools?

2. Which individual student characteristics predict performance on college admissions tests among Chilean high school graduates?

3. To what extent does the relationship between students' individual characteristics and their performance on college admissions tests vary across schools?

4. Which school characteristics explain the variability of students' performance on college admissions tests between schools?

5. To what extent do school characteristics influence the relationship between students' characteristics and their performance on admissions tests?

Statement of the Problem

In Chile, there is an achievement gap in college admissions test scores which correlates with students' family income, parental education, prior achievement in elementary and high school, and the type of school attended (Contreras, Corbalán, & Redondo, 2007; CTA-CRUCH, 2004; 2005; Koljatic & Silva, 2006; 2010; OECD & The World Bank, 2009). This admissions test gap decreases the chances that Chilean low-income, first-generation, and female students, as well as graduates of public and vocational high schools, will successfully progress through the Chilean admission process to the publicly funded universities in the country[1].

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[1] In Chile, publicly funded institutions are those created before Pinochet's educational reform of 1981. Among these institutions, 16 are public and 9 are private, usually referred to as "traditional" universities.

According to a recent report by the Organization for Economic Co-operation and Development and the World Bank (OECD & The World Bank, 2009), underrepresented students are less likely than their more privileged counterparts to earn the minimum score required to apply to publicly funded institutions and to be eligible for state financial aid (OECD & The World Bank, 2009). Moreover, when underrepresented students do meet these minimum requirements, they are still less likely to earn scores competitive enough to gain them admission to a traditional university (OECD & The World Bank, 2009).

Table 1 shows the number and percentage of applicants who took the admissions test, then applied to traditional universities, and finally enrolled at a publicly funded university in Chile in 2005. It can be observed that low-income students, females, and graduates of vocational and public high schools are left behind at higher rates in each of the steps and stages of the Chilean admission process than their respective counterparts. In 2005, of the 122,014 total applicants who took the test, only 42.5% applied to one of the traditional universities, and only 23.7% finally enrolled. Low-income students, females, and graduates of public and vocational schools dropped out of the admission process at a higher rate than their more privileged counterparts. Of the 67,753 low-income students who took the admissions test in 2005, 34.1% completed the application process, and only 19% enrolled in a publicly funded institution. These percentages are very similar for graduates from public high schools. In addition, graduates of vocational high schools dropped out of the admission process at the highest rate. Of the total of 27,014 graduates from vocational high schools who took the admissions test in 2005, 20.8% completed the application process, and only 10.3% finally enrolled. Also, although females applied at a higher rate than males (45.7% versus 44.1%), they finally enrolled in a lower proportion as compared to males (24.2% versus 25.9%).

Table 1. *Chilean applicants who took the admission tests, applied and enrolled to selective universities in 2005 (Valdivieso, Antivilo & Barrios, 2006).*

	Took the Test		Applied		Enrolled	
	N	%	N	%	N	%
Total	122,014	100.0	51,811	42.5	28,906	23.7
Student Characteristics						
Income						
Low	67,753	100.0	23,072	34.1	12,878	19.0
Middle	45,342	100.0	23,184	51.1	13,016	28.7
High	8,559	100.0	5,550	64.8	3,011	35.2
Gender						
Male	57,665	100.0	25,445	44.1	14,924	25.9
Female	64,349	100.0	26,366	45.7	13,982	24.2
School Characteristics						
School Sector						
Private	18,692	100.0	11,574	61.9	6,376	34.1
Private Subsidized	53,128	100.0	22,540	42.4	12,422	23.4
Public	50,194	100.0	17,697	35.3	10,108	20.1

Just two research papers (Contreras, Corbalán & Redondo, 2007; Valdivieso, Antivilo & Barrios, 2006) have investigated the achievement gap related to admissions tests. Although these studies have made a valuable contribution to the understanding of the inequalities associated with the admissions tests, they are methodologically constrained. Using data of students who took the admissions tests in 2005, Valdivieso, Antivilo, and Barrios (2006) conducted a quantitative study and found that test scores varied according to students' family income, parents' education, parents' occupational status, and the type of high school from which students graduated. However, these authors only used descriptive information to reach their conclusions; their study did not rely on statistical methods to determine the effect of variables on test performance, and

did not provide information about the statistical significance of the achievement gap between different groups of students. Therefore, it cannot be concluded with certainty that most of the variability of the admissions tests scores was due to systematic relations between test scores and student and/or school characteristics (Allison, 1998).

An additional study conducted by (Contreras et al., 2007), identified income, prior achievement in elementary school, high school GPA, and gender as the main factors influencing test scores among Chilean high school graduates. Contreras and associates also found that parental education and the type of elementary and high school students attended had a smaller but still statistically significant effect on test performance. This small predictive value of the school sector in Contreras, Corbalán and Redondo's model might be related to their use of linear regression models. This methodological approach tends to underestimate the effect schools can have on students' achievement because it ignores the clustered or nested nature of the data, i.e. students nested in schools (McCoach & Adelson, 2010). Another major flaw of Contreras, Corbalán and Redondo's model is that they did not use dummy variables to introduce categorical variables in the regression model. Instead, the categorical variables introduced in the model such as gender and parental level of education were treated as if they were continuous. This may have led these authors to an incorrect interpretation of the regression coefficients.

Problem Context

To better understand the nuances of the inequities of admissions tests in Chile, this section will first introduce the primary differences between the Chilean and American education systems. Then, it will refer to the Chilean admission process to traditional universities in greater detail. Finally, the college choice process of Chilean students and the role that college admissions tests play in that process will be discussed.

The American and Chilean Systems of Education. The Chilean and American systems of education have several characteristics in common, such as a similar K-12 system, a comparable structure of degrees in postsecondary education (associate, bachelor, master, and doctorate). Also, similarly to the United States, in Chile there are 1) public schools, which are tuition-free and publicly administered, 2) subsidized private schools, which are similar to charter schools, publicly funded by per-student vouchers and privately administered, and 3) private schools, which usually charge high tuition and are privately administered (Cabreba, 2010; OECD and The World Bank, 2009).

Nonetheless, there are four main differences between the two systems worth mentioning. First, while in the United States students usually attend a public school to which they have been assigned using a geographic criterion, in Chile, elementary and high school students have the opportunity to choose the public school they will attend (Gauri, 1999). Unlike in the United States, the majority of students are enrolled in the private subsidized sector. (Cabreba, 2010; OECD & The World Bank, 2009). There are two factors that usually play a role in students' school choice: 1) students' ability and/or willingness to pay tuition is a factor that limits their school choice, especially for low-income students, and 2) unlike the American system, which relies in lotteries when a school demand surpasses available seats, in Chile, the best public, private and subsidized private high schools administer entrance examinations for selection purposes (OECD & The World Bank, 2009) and this may also restrict students' school choice. In this case, the decision to enroll in a particular school is also limited by students' academic ability to gain admission to that school.

Secondly, in eighth grade Chilean students must choose whether to attend a college track or a vocational high school (Kis & Field, 2009). Therefore, those who

aspire to continue their education beyond high school may choose to attend college-track high schools, regardless their prior academic performance. Alternatively, students may decide to attend vocational high schools, which follow a curriculum that trains students to enter directly into the labor market and does not prepare them for the college admissions tests. Nonetheless, a high school diploma from a vocational school sufficiently fulfills college entrance requirements. In fact, in 2010, 30% of applicants who took the college admissions test graduated from vocational schools (DEMRE, 2011).

Third, unlike the American system of education in which curricula is primarily shaped by local school boards and state governments, in Chile, the elementary and secondary school curriculum is set by the national government's Ministry of Education (DEMRE, 2011; Gauri, 1999). Therefore, all students in college-track high schools follow the same mandatory curriculum. Because college admissions tests assess students' knowledge of the high school curriculum, all graduates from college-track high schools, in theory, should be equally prepared for college admissions tests and be ready for college after high school graduation.

Fourth, in Chile, publicly funded universities have a joint process of admissions which is centrally executed by an official national public agency, the Department of Evaluation, Measurement and Educational Records (DEMRE). This process is very bureaucratic in nature, because it involves a series of pre-established procedures set by the 25 institutions that designed this joint process of admission. All students must follow this process at the same time in order to apply to these universities. As such, unlike in the United States where students submit applications directly to the colleges in which they are interested, Chilean students must submit their college applications through DEMRE. DEMRE centralizes on a website the admissions requirements set by traditional

universities for each major, and allows students to set up a list of majors and universities to which they want to apply, indicating up to eight preferences in order of importance. Then, taking into account students' admissions test scores and high school GPA, and major admissions requirements, DEMRE tries to match students with the majors they most prefer and finally admits students to only one major at a particular university of the ones listed on their preferences. The admission process managed by DEMRE is explained in more detail in the next section.

The Chilean Admission Process. This section details the admission process centrally managed by the Department of Evaluation, Measurement and Educational Records (DEMRE). For purposes of clarity, this process is presented in five chronological stages or sub-processes: registration, examination, application, admission, and enrollment. The description of these sub-processes is based on the information available on the official DEMRE website (DEMRE, 2011).

Registration. In their senior year, from June to August, high school students must fill out registration forms and pay a registration fee through the DEMRE website. The registration process usually takes place in all high schools across the country where students are offered assistance filling out the registration forms. In 2010, the registration fee was approximately US$50. Low-income students from publicly funded high schools are eligible to apply for a fee waiver. Upon registration, applicants must choose one of the 166 test locations throughout Chile at which to take the admissions test. After registration, students can access a variety of online resources available on the DEMRE website, such as practice tests and a simulation web tool that allows students to predict their chances of getting into a certain major and a specific university using fictitious information regarding test scores and high school GPA.

Examination. College admissions tests consist of four standardized paper-based exams: 1) language, 2) math, 3) science, and 4) history and social sciences. The language and math sections of the test are mandatory, while the science and history and social sciences sections are optional, although students are required to take at least one of the optional sections of the test. These tests attempt to measure applicants' cognitive abilities, defined as their ability to recall information as it was learned, to conduct data analysis, to apply knowledge in problem solving, and to analyze, synthesize, and evaluate concepts, procedures, and problems. The questions are multiple-choice with five possible answers each, of which only one is correct. In order to factor in applicants' random answers, the final score is obtained by subtracting one quarter of all the wrong answers from the total number of correct answers. Then, the scores are standardized (z-scored) and adjusted so that the median is 500 score points and the standard deviation is 110 score points (the final score is 110*z-score + 500). The test scale has a minimum of 150 score points and a maximum of 850 score points.

Admissions tests are offered just once annually, at the end of the academic year, in December. The tests are taken simultaneously in the 166 designated test locations across the country. The examination process takes three days: the first day students attend an orientation session, the second day students take the language and science sections of the test, and the third day students take the math and history and social science sections of the test. If students do not complete the entire test-taking process, they are automatically eliminated from the admission process.

Application. Usually applicants can access their individual test scores results through the DEMRE website two to three weeks after the examination process. Once DEMRE posts the test score results on their website, students have a three-day timeframe

in which to complete the application process. Those applicants who obtain an average score greater than 450 score points on the language and the math sections of the test are allowed to go through the centralized application process managed by DEMRE, regardless of the score they obtained on the other two optional sections of the test. Using a web tool on the DEMRE website, applicants must set up a list of majors and institutions to which they want to apply, indicating up to eight preferences in order of importance. Figure 2 shows an example of an application form. Students who score below 450 score points on the math and language sections are automatically eliminated from the application process to traditional universities. However, they can apply to other less selective higher education institutions, or they can retake the admissions test and go through the annual DEMRE admission process as many times as they wish in the subsequent years.

17.250.526-3			Guevara Ramírez Tomás Andrés	
ID number			Name	

Pref	Code	Major	University	Campus
1	2173	Bioengineering	Univ. Tecnológica Metropolitana	Macul
2	1213	Forestal Engineering	Univ. Católica de Chile	Santiago
3	2145	Industrial Engineering	Univ. Tecnológica Metropolitana	Macul
4	1715	Industrial Engineering	Univ. Austral de Chile	Coyhaique
5	1781	Industrial Engineering	Univ. Austral de Chile	Miraflores
6	1614	Computer Science	Univ. de Santiago de Chile	Santiago
7	1808	Math Education	Univ. de Santiago de Chile	Santiago
8	1602	Business Administration	Univ. de Chile	Santiago

Figure 1. DEMRE Application form. Adapted from DEMRE, 2010.

Admission. Admission to publicly funded universities depends upon only two factors in the selection of students: applicants' scores in the college admissions tests and high school GPA (which are converted to score points using a scale similar to that of

admissions tests). However, each major within the traditional universities assigns different weights to these two selection factors. For example, at the Universidad de Santiago de Chile, the weights assigned to high school GPA, language, math, and science sections of admissions tests in electrical engineering are 25%, 10%, 40%, and 25%, respectively, while in elementary education they are 40%, 25%, 25%, and 10%, respectively. As such, an applicant might have different application scores when applying to different programs and institutions.

Using the weighted average application score as the criterion, applicants are sorted by DEMRE into majors until the available spots are filled, and the remaining applicants are put on a waiting list. The DEMRE tries to match students with the majors they most prefer. If an applicant is not sorted into the major listed as her first choice, then the system tries to match her with her successive preferences. If an applicant is admitted to a major high on her list of preferences, the rest of her preferences are discarded by DEMRE so that she is admitted to just one major at one institution. Then, a week after the application process is complete, applicants can access the DEMRE website to see their application results.

Enrollment. At this point, the DEMRE turns the process over to the 25 universities participating in centralized admission system. Each university sets an enrollment period during which students must decide whether to enroll in the program to which they were admitted. If an admitted student decides not to enroll, then the next applicant on the waiting list is admitted. All institutions try to fill their program spots by the end of the enrollment process.

The Chilean College Choice Process. The college choice process developed by Cabrera and La Nasa (2000) and Hossler and Gallagher (1987) is used here as a frame of

reference to describe in greater detail the Chilean admission process and students'

decisions involved in selecting an institution and major. This model conceives the college

choice as a three-stage process. In the first stage, students develop a predisposition for

college. This stage may take place over a long period, from seventh grade through high

school. The second stage involves seeking information in order to identify colleges to

apply, obtaining information about financial aid, and becoming academically qualified.

The third and final stage, choice, involves submitting college applications, college

enrollment and actual attendance.

 Although this model was developed to study the college choice process of

American students, it is also applicable to the Chilean admission system. Additionally,

because it is widely utilized, this model is likely familiar to the reader, which facilitates

the description of the Chilean college choice process despite its differences with the

American context. Also, given its simple three-stage structure, the college choice process

model is easily transferable to the Chilean context.

 Figure 2 depicts the three stages of the college choice process (top part of the

diagram) as a flowchart of sequential steps and decisions involved in the admissions

process. The numbered rectangles represent each of the five steps that students need to

follow to complete the admissions process: 1) registration, 2) examination, 3) application,

4) admission, and 5) enrollment. This diagram also provides details about the decisions

applicants must make concerning the admissions test throughout the stages of the college

choice process, which are represented by rhombuses in the flowchart. During the

predisposition stage, the first rhombus represents the decision students need to make

regarding the type of high school to attend (vocational or a college-track school),
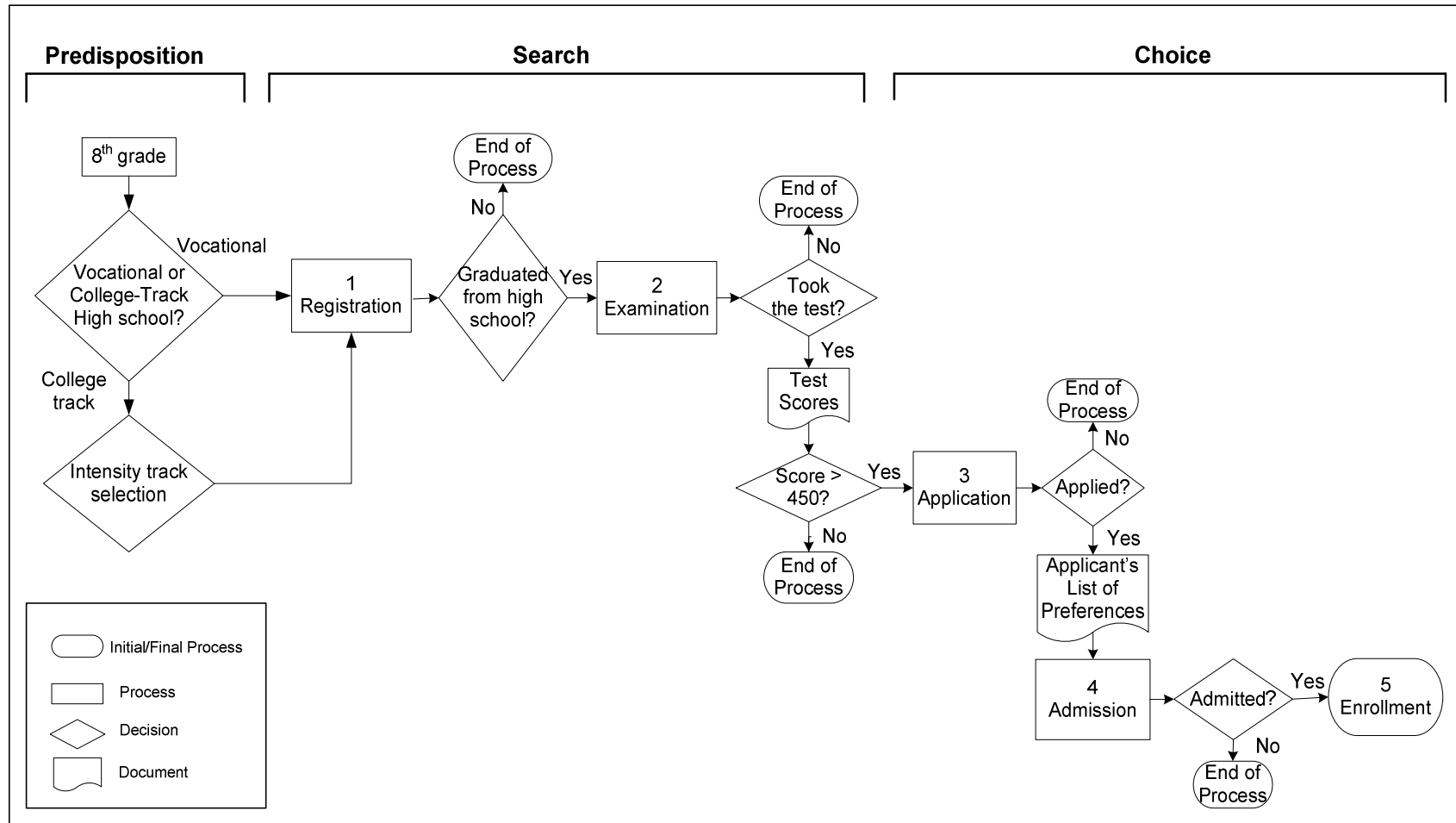
Figure 2. The Chilean admission process in terms of the college choice process

and the second one, the need to opt for an intensity track for those who previously chose to study at a college-track high school. During the search stage, students have to register for the test (rectangle 1), but only those who graduated from high school can actually take the test (rectangle 2). For those who took the test they can advance to the next stage only if they scored 450 score points in the test. In the third and last stage in *Figure 2*, choice, students need to go through the application process (rectangle 3). Those who completed their application would be considered for admission (rectangle 4). Finally, students admitted have to actually enroll to complete the process (rectangle 5). Following, I refer specifically to the stages of and decisions involved in the admissions process of Chilean students using the college choice process model as a conceptual frame.

Predisposition. The predisposition stage is the phase in which students' intentions to continue education beyond high school emerge, and it starts as early as seventh grade for American students (Hossler & Gallagher, 1987; Cabrera & La Nasa, 2000). Similarly, in the Chilean context, this stage starts in eighth grade, when students must choose whether to enroll in a college track or in a vocational high school. As noted by Cabrera and La Nasa (2000), in this stage students have already developed occupational and educational aspirations. It is not clear, however, what role occupational and educational aspirations play in Chilean students' decision to attend a vocational or a college track high school. However, what is known is that one third of Chilean students choose to attend a vocational school (Kis & Field, 2009). Although one may assume that Chilean students who decide to attend vocational high schools do not have aspirations to continue their studies beyond high school, the high percentage of them who take admissions tests suggests otherwise. In fact, in 2010, 30% of test-takers were graduates of vocational high schools. However, because admissions tests were explicitly designed

with the college track high school curriculum in mind, students who attended these high schools are often better prepared and thus more likely to attend college than vocational high school students (Koljatic & Silva, 2010).

During the predisposition stage, at the end of tenth grade, Chilean students who attend college track high schools must select an intensity track (math, biology, or social sciences) (MINEDUC, 2011). Therefore, by that time students must have an idea of the major or field of study in which they aspire to continue their higher education. This will help them to better prepare themselves for the subject area admissions tests associated with their desired major or field of study, although following a particular intensity track is not a college admission requirement. However, it is convenient to choose an intensity track aligned with one's occupational aspirations. For example, if a student aspires to study engineering it is convenient, but not mandatory, for her to follow the math intensity track.

Search. In this stage, students gather information about universities and decide to which universities they will apply (Hossler & Gallagher, 1987; Cabrera & La Nasa, 2000). In Chile, there are many reliable sources available to support students' search for information about majors, admissions requirements, types of higher education institutions, accreditation status, financial aid, and other kinds of information (OECD & The World Bank, 2009). These sources are mostly official government websites and media publications (OECD & The World Bank, 2009). However, it is unknown if and how Chilean students use the information available from these sources in their search for institutions and programs.

According to Cabrera and La Nasa (2000), becoming academically qualified and obtaining a high school diploma are critical steps for American students to enroll in a

postsecondary institution. Additionally, McClafferty, McDonough, and Nunez (2002) point out that preparing for and taking college admissions tests are also critical steps for American students on the path to college. Similarly, in the Chilean context, becoming ready for college requires graduating from high school and preparing for, registering for, and taking the admissions test. Although preparation for the admissions test may start earlier for some students than others, most private preparatory courses for admissions tests are offered to eleventh and twelfth graders. Those able to afford it usually enroll in these private preparatory admissions tests courses (Uribe & Salamanca, 2008). Others must rely on their high school preparation, which is unequal depending on the school sector (Uribe & Salamanca, 2008). DEMRE provides free-of-charge online practice tests to all applicants.

In this stage, a necessary step towards college for both vocational and college track high school graduates is to register for the admissions tests (process 1 in Figure 2). Once applicants register to take admissions tests they can predict their chances of getting into a certain major at a specific university using a simulation web tool on the DEMRE website. This tool, among other online resources available on the DEMRE website, is a very useful resource to help students select a list of majors and institutions they consider as potential alternatives to continue their studies after high school. Because Chilean universities admit students directly to majors, upon high school graduation students must have a clear idea of the major and the university in which they want to enroll.

The final step in this stage is taking the admissions tests (process 2 in Figure 2). Having actually taken the test becomes a critical step in the search process, because only after knowing their actual test scores can applicants make a more educated guess about the majors to which they have a chance of being admitted. In spite of that, a significant

number of students who register for the test ultimately do not actually take it. According to statistics from the DEMRE (2011), a total of 38,492 (13.3%) registered applicants did not take the test in 2010. The reasons why students behave this way have not been addressed in the literature. According to DEMRE (2011) statistics, in the last three years almost one third of test takers did not earn the minimum score for application to a major. For these students, this is the end of the admissions process. There are also an unreported number of applicants who earn the minimum score but do not move forward in the application process, which is the first step of the next stage.

Choice. In this stage, applicants must apply to a set of institutions and decide which institution to attend (Cabrera & La Nasa, 2000). As stated before, the application to Chilean universities (process 3 in Figure 2) is done through the DEMRE website. Students must identify up to eight preferences of majors and institutions in order of importance. In 2005, only 42.5% of the students who registered to take the test completed the application process. Low-income students, and graduates from public and vocational high schools completed the application process at a lower rate than the average, with a 34.1%, 35.3%, and 20.8% completion of the application process, respectively (Valdivieso, Antivilo & Barrios, 2006).

Regarding the choice of institution and program, in the Chilean context it is the centralized system managed by DEMRE which makes the decision on behalf of the applicants in the admission process (process 4 in Figure 1) based on students' admissions test scores and stated preferences. It is important to note that the DEMRE system admits applicants into only one of their preferred programs. However, a significant proportion of students are not admitted to any program, either because they did not meet the minimum admission requirements set by the universities for each major, or because their

application scores were not competitive enough to gain them admission to the majors

listed in their preferences. The final process of this stage is actual enrollment and

attendance in a particular institution (process 5 in Figure 2). In 2005, only 23.7% of

registered applicants finally enrolled in a publicly funded university, and the proportion

of applicants enrolled was lower for students who are low-income (19%), and graduates

of vocational (10.3%) and public (20.1%) schools than for high-income students (35.2%)

and graduates from college-track (27.5%) and private (34.1%) high schools (Valdivieso,

Antivilo & Barrios, 2006).

Conceptual Model

Based on the American and Chilean literature on this topic (e.g. Adelman, 2006;

Contreras et al. 2007, 2009; Lee, Bryk, and Smith, 1993; Zwick, 2002), I hypothesized

that both individual agency and school characteristics would have an effect on student

performance. Consequently, I proposed a conceptual model that advances a structure

whereby students are nested within schools. This model assumes that: 1) at the school

level, students are affected by the particular contexts of their respective schools, not only

by the structural school characteristics but also by the aggregated social and academic

characteristics of their peers, as well as school practices and policies; and 2) at the

individual level, socioeconomic status, academic achievement, and demographic

characteristics impact student performance on admissions tests. Finally, the model

assumes that there are cross-level interactions; i.e., that some school characteristics and

aggregates of student characteristics may influence the relationship between students'

predictors and outcomes.

Figure 3. Conceptual model

Building upon Existing Literature

In the last three decades, multiple studies (Beyer & Le Foulon, 2002; Fontaine, 2002; Gil & Grez, 2002; Gil & Ureta, 2003; Le Foulon, 2002) documented the highly unequal results of admissions tests and consequences of this inequality for access to Chilean higher education. However, since the admissions test model was reformulated in 2003, similar research is scarce. This study will significantly contribute to the reduction of this dearth in the literature in three ways. First, this work will go beyond descriptive statistics. As such, it will provide explicative evidence about the school- and individual-level factors that predict performance on admission tests and that contribute to the achievement gap. Second, this study will address a methodological flaw of prior research that has ignored the nested nature of educational data and thus potentially underestimated the effect of the school on individual performance. The use of HLM techniques allows for the maintenance of the assumption that applicants' scores are not independent from

the scores of their classmates at school, and the estimation of the actual effect the school has on individual performance. Finally, this study will explore the effect of school conditions and characteristics on performance on admissions tests that have not been included in prior studies. As such, this study will contribute to a better understanding of the role that schools play in the preparation and success of students on admissions tests.

Methods

This work will utilize hierarchical linear modeling techniques (HLM) and HLM 7 software to obtain a multilevel model of individual and school factors that simultaneously explain the variability of the students' scores on admissions tests. HLM is a suitable approach for this study because these techniques allow for the consideration of the nested nature of the data, i.e. students nested within schools.

HLM techniques allow researchers to avoid methodological constraints of prior studies related to the underestimation of school effects and violation of the independent observations assumption. By using HLM techniques these methodological nuisances are not problematic because in multilevel linear models student performance on admissions tests at the individual level is modeled in terms of both student- and school-level variables "while concurrently estimating and adjusting for the amount of intraclass correlation present in the data" (Hedeker & Gibbons, 1994, p. 758). HLM also allows researchers to model data for a varying number of students within each school.

This study draws from two main Chilean datasets: PSU and SIMCE. The Admissions test (PSU) dataset, hereafter called the PSU dataset (PSU stands for Prueba de Selección Universitaria, meaning college admissions tests) contains information about all Chilean high school graduates (approximately 249,000 applicants) who registered to take the college admissions tests in Chile in 2009. This study also draws from the prior

achievement (SIMCE) dataset. SIMCE is the Department of Learning Outcomes Assessment of the Chilean Ministry of Education. SIMCE standardized tests assess the achievement of fundamental objectives and minimum compulsory contents of the current national curriculum in math, language, natural sciences, and social sciences. These tests are administered nationwide once a year to fourth graders, and every other year to eighth and tenth graders. This dataset which contains information about approximately 245,000 tenth graders who took the SIMCE math and language tests in 2006, distributed across approximately 2,500 schools.

In the data preparation stage of this study, I examined these datasets prior to model testing to judge the extent to which it meets important assumptions needed when using regression based methods. To verify the assumption of normality, I combed the data for potential outliers and skewness. I also examined the potential presence of multicollinearity among my variables. And, then, I examined amount and patterns of missing data. I used a single imputation in SPSS 20 to address instances of missing data within the sample. I decided to exclude from the sample vocational students and students who graduated from high school prior to 2009. The final sample for the study was comprised 106,000 students from 1887 schools.

Practical Implications

The findings of this study are especially relevant to policymaking. Although the inequalities in access to Chilean publicly funded universities have not gone unnoticed by the Chilean government, some policies regarding admissions, financial aid, and public funding appear to be misaligned with the government's efforts to reduce inequality of access to higher education. The results of this study provide reliable figures that evidence the need to reconsider current financial aid and admissions policies in order to increase

access to higher education for traditionally excluded groups in Chilean society. As previously stated, admissions tests are not only a requirement for admissions purposes, but also to apply for state financial aid. Therefore, having a better understanding of how unequal the admission tests are, and the groups of applicants that are most negatively affected by these tests, might help policymakers to better target public resources and to make progress towards greater equality of educational opportunities.

Additionally, the results of this study have implications for public funding of Chilean higher education. Since 1981, a performance-based funding method allocates per-student subsidies to all institutions of higher education able to enroll applicants from the group of 27,500 who scored highest on the admissions tests (Hudson, 1994). The conclusions of this study provides solid arguments to eliminate or change this public subsidy that offers incentives to institutions to continue denying access to applicants coming from the most disadvantaged sectors of Chilean society.

Summary

This study builds upon previous literature in the areas of school effectiveness, access to higher education, and factors affecting performance in standardized tests to better understand the extant achievement gap in college admissions tests in Chile. A thorough review of this literature is presented in the next Chapter.

Significant contributions can be made in this area by using a multilevel model approach to examine the school and student characteristics that impact performance in college admissions tests among Chilean high school graduates. Multilevel models allow for the simultaneous estimation of school-level and student-level effects, which do not underestimate school effects and takes into account the nested nature of the data. Chapter 3 provides a detailed outline of the multilevel approach used in this study.

Then, Chapter 4 is organized to initially provide a descriptive analysis to portray the main characteristics of schools and students included in the sample in relation to the outcome variable. Next, I briefly describe the steps followed in the specification of the model and summarize the findings of the final random intercept and slopes model. Finally, the last section of this chapter provides answers to each of the study's five research questions.

Finally, Chapter 5 presents a discussion of the findings. The main findings of this study indicate that the type school attended is responsible for more than a half of the variability in students' scores on admissions tests. Although students may improve their performance in admissions tests by putting their best effort in their academic performance in high school, students' performance on college admissions tests depends mostly upon the average socioeconomic status and sector of the school they attended. These findings offer insights to practitioners and policymakers regarding the changes that are needed in admissions and financial aid policies to attain the Country's goal of providing equality of educational opportunity.

Chapter 2: Review of the Literature

This chapter discusses the theoretical and conceptual frameworks that guided the construction of the conceptual model proposed for this study. I chose as a main frame of reference McDonough & Fann's taxonomy (2007) of the literature on access to higher education. These authors provide a succinct but complete review of the literature addressing the main factors which contribute to the persistent inequality of access to higher education in the United States. These authors classify the literature into three main categories: 1) individual-level studies, which refer to the students' attributes as the key determinants of access to higher education, 2) organizational-level studies, which denote the impact that educational institutions have on structuring students' opportunities to access higher education, and 3) field-level analyses, which focus on the reciprocal influence of students and educational institutions on each other, and the impact of this relationship on college access. These categories will serve as the main guidelines for the organization of this literature review.

Individual-Level Factors

According to McDonough and Fann (2007), individual-level research on access to higher education has been mainly influenced by two traditions. First, based on sociologic theories, research at the individual level has usually focused on how socioeconomic status, gender, and race influence the process students follow to gain access to higher education. Second, the research on access to higher education has also examined the psychological aspects of the stages students experience on their path to college (McDonough & Fann, 2007). Likewise, the literature on students' performance on standardized tests, particularly on college admissions tests, usually follows one of these

two approaches to explain the effects of individual characteristics on students' test performance.

Socioeconomic Status. There is widespread agreement among researchers that socioeconomic status is a determinant of access to higher education (Astin & Oseguera, 2004; Cabrera & La Nasa, 2000; Kezar, 2010; McDonough & Fann, 2007; Terenzini, Cabrera, & Bernal, 2001; Walpole, 2003; 2007). Students coming from the more disadvantaged sectors of the society have usually developed lower educational aspirations and exhibit lower educational attainment than their more affluent high school peers prior to and during college (Terenzini et al., 2001; Walpole, 2003), and their college choice process is difficult because of their limited knowledge about college and concerns related to their ability to pay for tuition or get financial aid (Cabrera & La Nasa, 2000; Terenzini, Cabrera & Bernal, 2001). It has been shown that taking the necessary steps to meet college admission requirements, like taking college admissions tests, help students of lower socioeconomic status to increase their participation in higher education (Cabrera & La Nasa, 2000). Unfortunately, low-income students tend to score lower than middle- and high-income students on college admissions tests (Bowen, Kurzweil, & Tobin, 2005; Kezar, 2010; The College Board, 2010), which constrains their college options.

As in the United States, access to Chilean higher education remains dependent upon students' socioeconomic status (Pitton, 2007). Although participation of all socioeconomic groups in postsecondary education has increased in the last two decades, high-income and middle-income students have gained disproportionate access as compared to low-income groups (Espinoza, 2007). Uribe, Espinoza, and González (2008), using data from the national survey of socioeconomic characterization from 1990 and 2003, found that students' probability of completing high school is mostly

determined by their parents' level of education. In relation to the probability of students to access higher education, these authors found that students whose parents are blue-collar workers are less likely to access higher education. The authors also corroborated that access remains unequal when taking into consideration household income, with students from the wealthiest families having a higher probability to access higher education. Additionally, Valdivieso, Antivilo and Barrios (2006) found that parental level of education and household income also influence students' probability of taking the admissions test, applying to an institution, and finally enrolling in a postsecondary institution.

Gender and Race. Standardized tests have long been criticized as a deterrent to access to higher education for racial minority and female students because they tend to obtain lower scores than their counterparts on such tests (Janesick, 2001; Forest & Kinser, 2002; Salkind, 2008). As a consequence, a large body of research has focused on determining whether college admissions tests over- or under-predict college performance during the first year for minority and female students (Mattern et al., 2008; NACAC, 2008; Zwick, 2002). The performance gap between students of different backgrounds on standardized tests has been attributed to diverse factors, such as language proficiency, course-taking patterns in high school, societal stereotypes, and test bias (Forest & Kinser, 2002; McKay et al., 2003). Some researchers have even suggested that genetic differences may also play a role in the disparate admissions test performance of students of different races and gender (e.g. Rushton, Skuy, & Fridjhon, 2002; Rushton, Skuy, & Bons, 2004). However, this type of research has been largely questioned and discredited (Cronshaw et al., 2006; Forest & Kinser, 2002; Wicherts & Johnson, 2009) because of being methodologically flawed and openly racist. According to Cronshaw et al. (2006),

"Rushton's work on intelligence testing and race contains fundamental errors, inappropriate conceptualization of ''race,'' inappropriate statistical comparisons, misuse of sources, and flaws of logic of a very serious nature" (p. 285), and that this line of research "is part of a long tradition of scientific racism in psychology" (p. 285).

In Chile, there is a significant admissions test performance gap between male and female students. In the last few years, it has been reported that male applicants have persistently scored one third of a standard deviation higher than female applicants on the admissions tests (CTA-CRUCH, 2004; 2005). In terms of race, although Chile officially recognizes the existence of Amerindian ethnicities, the State does not use race as a criterion to categorize the population (Hoberman, 2007). In the last Census, only 4.6% of the Chilean population self-identified as indigenous (INE, 2003). Moreover, Chile is considered to be a very homogenous country in terms of race and ethnicity, constituted of 95% White-Amerindians (Cruz-Coke & Moreno, 1994; Lizcano, 2007). Quijano and Ennis (2000) attribute this homogeneity of the Chilean population to a historic process developed in the first decades of the twentieth century:

"The situation in the countries of the so-called Southern Cone of

Latin America (Argentina, Chile, and Uruguay) was similar to what

happened in the United States. Indians, for the most part, were not

integrated into colonial society, insofar as they had more or less the same

social and cultural structure of the North American Indians. Socially, both

groups were not available to become exploited workers, not condemnable

to forced labor for the colonists. In these three countries, the black slaves

were also a minority during the colonial period, in contrast with other

regions dominated by the Spanish or Portuguese. After independence, the

dominants in the countries of the Southern Cone considered the conquest

of the territories that the indigenous peoples populated, as well as the

extermination of these inhabitants, necessary as an expeditious form of

homogenizing the national population and facilitating the process of

constituting a modern nation-state "*a la europea*." ... These countries also

attracted millions of European immigrants, consolidating, in appearance,

the whiteness of the societies of Argentina, Uruguay, and Chile." (p. 562).

I believe that this historic process of homogenization resulted in a population

difficult to classify in terms of race. This is probably why Chile lacks of an

institutionalized concept of race categories. Because of this, no Chilean studies

incorporate race as an explanatory variable.

Academic Preparation. There is wide agreement among researchers that one of

the most critical factors to students' gaining access to and persisting in college is the

quality and intensity of high school academic preparation, which is usually measured as

the highest level of mathematics a student has reached (Adelman, 2006; Cabrera,

Burkum, & La Nasa, 2005; DesJardins, Ahlburg, & McCall, 2002; Ishitani, 2006;

Pascarella & Terenzini, 2005). However, because "not all high schools present adequate

opportunity-to-learn, and some groups of students are excluded more than others"

(Adelman, 2006, p. xviii), academic preparation is not necessarily a factor that can be

addressed by individual agency. In Chile, all students must follow the same compulsory

curriculum. However, because some Chilean schools are not able to teach the full

compulsory curriculum (OECD & The World Bank, 2009), students attending those

schools may not receive the same academic preparation quality and intensity as students

at other more resourceful schools. Therefore, the quality of academic preparation that a

student receives is beyond her individual control and depends on the degree to which her school was able to cover the content of the curriculum (Vargas, 2010).

Test coaching, another form of academic preparation, has been found to improve American students' performance on college admissions tests (Zwick, 2002; Briggs, 2004). Because test coaching schools are usually expensive and more likely to be accessible to more affluent test-takers (Buchmann, Condro, & Roscigno, 2010), low-income students are at disadvantage. Similarly, in Chile most high-income students pay additional tuition to attend private test preparation schools, while this kind of academic preparation is unthinkable for low-income students (OECD/The World Bank, 2009; Williamson & Rodríguez, 2010). Although there is not much evidence regarding the effects of test coaching in the Chilean context, it is widely believed that this preparation is absolutely necessary in order to earn competitive scores on the admissions tests (Williamson & Rodríguez, 2010).

Academic Achievement. Academic achievement is considered a product of academic preparation and a factor positively associated with college enrollment (Cabrera & La Nasa, 2000; Perna, 2004; Terenzini, Cabrera & Bernal, 2001), and it is usually measured using high school GPA, class ranking, or standardized test scores as a proxy (Adelman, 2006; Perna, 2004). These measures of academic achievement are also typically used as factors of predictive validity of college success (Fleming, 2002; Hoffman & Lowitzki, 2005; Mattern et al., 2008; Temp, 1971; Zwick, 2002; 2004). The relationships that might exist between academic achievement in high school and students' performance on college admissions tests have not been addressed in the American literature. In Chile, high school GPA, class ranking, and standardized test scores have

been found to be predictors of college performance, although there is still disagreement

about which one is the best predictor.

Parental Involvement. In general, the literature has found that the more involved

parents are in the educational experiences of students, the more students get academic

advantages from those experiences (Lee, Bryk, & Smith, 1993). Parental involvement is a

broad concept and it has been defined in several ways, representing different parental

behaviors and practices (Fan & Chen, 2001). Examples of these are parental aspirations

of educational attainment, parental communication with students about school and

college, parental participation in school activities, parental communication with teachers

about students, and parental home supervision of homework (Fan & Chen, 2001).

School effectiveness research often refers to parental involvement as home

support for learning. Christerson and Sheridan (2001) summarize the ways in which

families can support learning at home (e.g., monitoring how time is spent at home,

reading with children, orienting a child's attention to learning opportunities), and allege

that what parents do to support learning at home is a better predictor of academic

achievement than parental status variables. However, Christerson and Sheridan indicate

that there is no agreement among researchers on the precise way in which parents

facilitate learning at home. Similarly, Marzano (2007) identifies three aspects of the

home environment that are supportive of academic achievement: 1) the frequency of

discussions with children regarding school, 2) the extent to which parents monitor their

children's activities (e.g., time spent doing homework, how much their children watch

television, and what type of programs they watch), and 3) parenting styles, whether they

be authoritative, authoritarian, or permissive.

Research on college choice and access has shown that parents' encouragement and educational aspirations (Cabrera & La Nasa, 2000; McDonough & Fann, 2007; Tierney, Corwin, & Colyar, 2004) highly impact student achievement and college enrollment. Parents who have a college degree are able to help their children in their college choice process, while first-generation students whose parents are less knowledgeable about college are more likely to rely on school counselors' guidance instead (Tierney, Corwin, & Colyar, 2004).

Siblings in Higher Education. Parents are not the only ones who influence the aspirations and educational performance of their children. Students who have older siblings in college are encouraged and aided by those siblings on the path to college (McDonough & Fann, 2007; Tierney, Corwin, & Colyar, 2004). A study by Loury (2004) showed that having older siblings with more years of education increases the probability that racial minority students will enroll in college. Widmer and Weiss (2000) showed that low-income students who are assisted by their older siblings have higher levels of academic achievement. In fact, these authors argue that the older sibling effect on these students is the most significant factor in their academic achievement.

Test Anxiety and Stereotype Threat. A great deal of literature has been dedicated to the study of how psychological and behavioral factors may affect students' performance on standardized tests. Text anxiety is probably one of the most recognized factors that negatively affect performance in evaluative situations, particularly in standardized tests. Test anxiety is composed of two dimensions: emotionality and worry (Cassady & Johnson, 2002; Spielberger & Díaz-Guerrero, 1990). Emotionality refers to physical responses experienced during examinations (e.g. dizziness and nausea). Worry, which is a cognitive realization of anxiety during evaluative tasks, is usually evidenced

by examinees experiencing distracting thoughts, such as considering the consequences of poor performance, like causing sorrow for their parents (Cassady & Johnson, 2002; Spielberger & Díaz-Guerrero, 1990. Some researchers have tried to identify additional components of the cognitive dimension of test anxiety, such as fear of failure (McCarthy & Goffin, 2005) or irrelevant thinking (Sarason, 1984). Following this line of research, Kim & Dembo (2001) investigated the influence of social-cognitive factors on students' performance on college entrance exams in South Korea. Kim and Dembo's results showed that parental psychological control negatively affected students' performance on admissions tests, while self-efficacy had a positive effect on students' performance on the college entrance exam. Similarly, Marsh et al. (2005), using longitudinal data from two nationally representative samples of German seventh graders, found that higher levels of self-concept of academic ability had a significant and positive impact on standardized test scores.

Another factor that has been found to be negatively associated with performance on standardized tests is stereotype threat (McKay et al., 2003), which is a concept borrowed from social psychology that has been offered as a possible explanation for subgroup differences in testing (Sawyer & Hollis-Sawyer, 2005). Stereotype threat reduces cognitive ability (McKay et al., 2003) "when a person enters a situation in which a stereotype of a group to which the person belongs becomes salient, concerns about being judged according to that stereotype arise and inhibit performance" (Sackett, Hardison, & Cullen, 2005, p. 7). In a seminal paper in this field of study, Steele & Aronson (1995) reported the results of an experimental study in which Black and White students were exposed to slightly different types of instructions which introduced or lifted stereotype threat. These authors concluded that stereotype threat "can impair the

intellectual test performance of Black students, and that lifting it can dramatically improve that performance" (Steele & Aronson, 1995, p. 808). In a similar study, Good, Aronson, and Inzlicht (2003) demonstrated that stereotype threat can also explain differences in math test scores between males and females. However, in the specific context of college admissions tests, there has been little research conducted to test the effects of stereotype threat. A study conducted by Cullen, Hardison and Sackett, (2004) included a post hoc analysis of the SAT and found no evidence to support the theory that the differences in the average SAT scores of minority students and females and the scores of male non-minority students could be due to stereotype threat. Similarly, Sackett, Borneman, and Connelly (2008) and Zwick (2002) do not agree that stereotype threat can explain differences in SAT scores among subgroups of students. These researchers argue that if stereotype threat is the reason minority students obtain lower scores on the SAT than their true scores, then the college performance of minority students should be underpredicted by this test. However, according to these authors, there is strong evidence in the literature which suggests that the SAT overpredicts the college performance of minority students. Therefore, for those authors it seems unlikely that stereotype threat has a significant impact on the test scores of minority students.

School-level Factors

In order to look for school-level factors affecting students' performance on standardized tests, I turned to the literature on school effectiveness and improvement research, which is dedicated to the investigation of the relationship between school characteristics and student outcomes (Ma, Ma, & Bradley, 2008; Scheerens, 1990), usually measured by student test scores on standardized achievement tests. Early research on the impact of school characteristics on student outcomes (Coleman et al.,

1966; Jencks et al., 1972) indicated that the effects of students' socioeconomic backgrounds were significantly larger than the effects of their school on educational outcomes (Gamoran, Secada, & Marrett, 2010). More recent advances in statistical methods that allow for the consideration of the nested nature of educational data have permitted researchers to better assess the effects of school factors on student achievement, which might have been overlooked in previous research (Ma, Ma, & Bradley, 2008).

Most of the research conducted about school effectiveness and improvement categorizes variables as context, input, process, and output quantitative indicators of schools (Bosker & Scheerens, 1994; Brophy, 1988; Hulpia & Valcke, 2004; Madaus, 1980; Scheerens, 1990, 1991, 1997; Van Petegem, Aelterman, Van Keer, & Rosseel, 2007), which is often referred to as the CIPO model. Alternatively, other studies classify school variables according to the structure and culture of the school (Hargreaves, 1995; Lee, Bryk, & Smith 1993; Ma, Ma, & Bradley, 2008; Newmann, Rutter, & Smith, 1989). These two views on schools are explained in more detail in the following section. Then, a description of the most frequently included variables in school effectiveness and improvement research is presented.

Context-Input-Process-Output Model. Also referred to as the CIPO school model (Scheerens, 1990, 1991; Teddlie & Reynolds, 2007), this framework of school effectiveness categorizes school variables as context, input, process and output indicators. Usually, studies based on the CIPO model conceptualize schools as multilevel structures, where schools are nested in contexts, classrooms are nested in schools, and students are nested in classrooms or teachers (Scheerens, 1997). The most utilized output variable is student achievement on standardized tests (Madaus, 1980; Rumberger & Palardy, 2005),

although other studies have focused on different outcome variables such as school

dropout rates (e.g., Croninger & Lee, 2001; Lee & Burkam, 2003), absenteeism (Bryk &

Thum, 1989; Phillips, 1997), and engagement (Lee & Smith, 1993). Also, a small but

increasing body of research has recently focused on other non-academic outcome

measures, such as student wellbeing (Hofman, Hofman, & Guldemond, 1999; Konu,

Lintonen, & Autio, 2002; Opdenakker & Van Damme, 2000; Van Petegem et al., 2007).

Context variables are often related to compositional characteristics of the school

community (parents and students), the neighborhood in which the school is located, the

characteristics of the school district, and school funding determined by the federal and

state governments (Scheerens, 1990, 1997). Input variables usually refer to the

characteristics of the teacher body, school resources and expenditures, and parental levels

of involvement and support. Process variables attempt to measure the activities,

behaviors, and interactions that occur in the schooling process (Madaus, 1980). Process

variables are more difficult to define because they often involve complex procedures of

data collection and measurement (Scheerens, 1991). As a consequence, a broader range

of measures and definitions are found in the literature for process variables than for input

and context variables. For example, Scheerens (1997) includes in this category measures

of leadership, curriculum quality, atmosphere, and teachers' working styles, while

Reezigt, Guldemond, and Creemers (1999) identify quality of instruction (curriculum,

grouping procedures, and teacher behavior), time for learning, and opportunity to learn as

the main process variables affecting student achievement.

School Structure vs. School Culture. The study of school effects has been

influenced by two main theoretical approaches. One approach has focused on the impact

of school structures, resources, constraints, and contingencies on student outcomes

(McDonough, 1998). From this point of view, which is referred to as the bureaucratic (Lee, Bryk, & Smith, 1993) or structural (Bolman & Deal, 2003; Ma, Ma, & Bradley, 2008) perspective, schools are seen as formal organizations in which goals, authority, rules, and roles are clearly defined (Bolman & Deal, 2003; Lee, Bryk, & Smith, 1993). Alternatively, another perspective has emphasized the role of school culture (McDonough, 1998). From this viewpoint, which is also referred to as the communitarian perspective (Lee, Bryck, & Smith, 1993; Phillips, 1997), school culture is seen as a set of implicit rules, traditions, and norms that shape the way in which members of that community behave (Deal & Peterson, 2009). As such, cultural patterns have a strong impact on outcomes and performance (Deal & Peterson, 2009). Consequently, measures of school structure usually relate to aspects of a school that are beyond the control of school members (Ma, Ma, & Bradley, 2008), while school culture measures generally refer to aspects of the school that can be manipulated (Ma, Ma, & Bradley, 2008; Scheerens, 1990).

School structure is usually described in terms of school resources, characteristics of the student body, and characteristics of the teacher body (Ma, Ma, & Bradley, 2008). As such, variables of school structure are usually expenditures per student, school geographical location, school sector, composition of the student body, teachers' education, teachers' experience, and average school achievement on standardized tests (Kang, Rowan, & Raudenbush, 2004; Lee, Bryk, & Smith, 1993; Ma, Ma, & Bradley, 2008; Scheerens, 1990).

In Chile, studies of students' performance on the admissions test (CTA-CRUCH, 2004; 2005; OECD & The World Bank, 2009) have found that school sector has a strong impact on students' performance on admissions tests. Students attending public high

schools have consistently scored lower on admissions tests than students attending private and subsidized private schools. Another school characteristic that matters in admissions test performance is the curricular emphasis of the school (vocational versus college track high schools). Chilean studies (Contreras et al., 2007; OECD & The World Bank, 2009; Valdivieso et al., 2006) have shown that students from vocational schools typically score lower on admissions tests than students from college-track high schools.

Research on school culture has found a relationship between certain variables related to school culture that make a school more effective. The most mentioned characteristics are a strong principal's leadership, high expectations for student achievement, a safe and orderly learning environment, permanent monitoring of student progress, clear educational goals, and strong parental involvement (Brophy, 1988; Davis & Thomas, 1989; Lee & Croninger, 1994; Ma, Ma, & Bradley, 2008; Scheerens, 1990). To my knowledge, there have been no studies done in Chile that have examined the impact of school culture variables on student achievement, as measured by admissions test scores.

Another useful classification of school variables, which includes variables of both structure and culture of the schools, is provided by Lee and Croninger (1994), who categorized school characteristics into three types: 1) school composition and structure, which refer to average characteristics of the teacher and student bodies, such as the proportion of poor and minority students the school sector, and whether the school is located in an urban or a rural setting; 2) school conditions, which describe a school's environment and organization, such as parental satisfaction with the school and orderliness of the school's environment; and 3) school policies and practices, such as

cooperation and coordination among teachers and whether the school groups students according to their ability.

School-Level Variables. There is a significant overlapping of school variables considered in both the CIPO model and the structure/culture organizational view of the school. In this section I describe school variables that are most frequently incorporated in both approaches.

Student Achievement. Most studies on school effectiveness have traditionally used student achievement on standardized tests as the outcome or dependent variable (Madaus, 1980; Rumberger & Palardy, 2005). More recently, researchers have also started focusing on other non-cognitive outcome measures, such as student wellbeing (Hofman et al., 1999; Konu et al., 2002; Opdenakker & Van Damme, 2000; Van Petegem et al., 2007). However, student achievement, measured by student performance on standardized tests, still prevails as the main focus of school effectiveness research (Hill, Rowan, & Ball, 2005; Hill & Rowe, 1996; Hoy, Tarter, & Hoy, 2006; Miller & Rowan, 2006). Most research conducted in this field draws from national and international longitudinal datasets of the National Center for Education Statistics (NCES), such as PISA, ECLS and NELS.

Prior Achievement. Usually, most school effects studies control for student socioeconomic background and for prior achievement in order to reflect differences in student intake characteristics (Hill & Rowe, 1996). Usually, prior achievement is measured by school grades and/or by standardized test scores (Pinxten et al., 2010). By including prior achievement, researchers prevent threats to the internal validity of their models (Teddlie & Reynolds, 2007). However, some researchers argue that including some measures of prior achievement may result in the underestimation of school effects,

especially when the measure of prior achievement considered is too proximal to the point at which the effects are being measured (Cuttance, 1985; Teddlie & Reynolds, 2007).

Compositional Characteristics of the Student Body. Aggregated measures of student characteristics are typically included in school effectiveness research because it is usually the case that an aggregated characteristic of the student body (e.g., socioeconomic status) has an effect above and beyond the effect of the same variable at the individual level (Teddlie & Reynolds, 2007). These measures usually are aggregated socioeconomic status and proportion of minority students in the school. Lee and Croninger (1994) argue that high concentrations of disadvantaged students in a school may have a negative impact on students' motivation and classroom instruction, as many of these students require more support from teachers than other more affluent students to maintain an appropriate learning pace. The effects of compositional variables are often called context or compositional effects (Luke, 2005; Raudenbush & Bryk, 2002; Teddlie & Reynolds, 2007).

School Resources. An important amount of research within the school effectiveness field is focused on determining the effects of school resources on student achievement. School resources are usually measured in terms of per student expenditures, teacher-pupil ratio, class size, average teacher salary, books and materials, and capital outlays per pupil, among other considerations (Grubb, 2008; Levacic, 2007; Rumberger & Palardy, 2005). The available evidence indicates that additional resources allocated to schools do not necessarily translate into improved student achievement (Levacic, 2007). Moreover, most research on school effectiveness has failed to establish a causal relationship between financial resources and student achievement (Teddlie & Reynolds, 2007). However, additional resources targeted to specific goals, such as assisting more

socially disadvantaged pupils, have a greater effect than a general increase in spending

from current levels. For schools which already have a relatively high level of funding, an

increase in financial resources will produce positive but relatively small effects (Levacic,

2007).

School Climate. There is a wide range of definitions and variables of school

climate that have been incorporated into school effectiveness research (Anderson, 1982;

Kyriakides et al., 2010). An early comprehensive review of the literature on climate and

its effects on student achievement was conducted by Anderson (1982). According to

Anderson, a widely accepted definition of school climate is consistent with Tagiuri's,

who asserts that climate is the environmental quality of an organization that has four

dimensions: ecology, milieu, social systems, and culture. Findings in research on school

climate differ depending on the dimension emphasized, the variables used to

operationalize such dimensions, and the way in which those variables are measured.

According to Anderson, most school climate instruments tend to ignore the dimensions of

ecology and milieu, while the majority of factors measured by school climate instruments

seem to fall into the social system and culture dimensions. In a more recent review of the

literature, Kyriakides et al. (2010) found a wide range of school climate factors

incorporated in effectiveness models. According to these authors, the more narrow

definition of school is provided by Creemers, who defines school climate in terms of five

aspects: 1) student behavior outside the classroom, 2) teacher collaboration and

interaction, 3) the relationship of the school with the community and parents, 4) learning

resources provided to students and teachers, and 5) values that facilitate learning

(Kyriakides et al., 2010). MacNeil, Prater, and Busch (2009) provide another definition

that makes a distinction between school culture and climate; the former refers to a set of

norms, values, and beliefs, while the latter is the shared perceptions of the school members' behavior. As such, climate is a result of school culture. MacNeil and colleagues identify ten dimensions of school climate (goal focus, communication adequacy, optimal power equalization, resource utilization, cohesiveness, morale, innovativeness, autonomy, adaptation, and problem-solving adequacy) based on the Organizational Health Inventory (OHI) to assess how the school climates of these three categories of schools are similar or different.

Principal's Leadership*.* In a recent review conducted by Kyriakides et al. (2010), these authors found that variables related to leadership have been included in most school effectiveness studies in the last two decades. However, "the results of this meta-analysis revealed that leadership has a very weak effect on student outcomes. Moreover, its effect seems to disappear in secondary education and in some educational contexts" (Kyriakides et al., 2010, p. 820). These results are consistent with Leithwood and Jantzi's study (2006) of the effect of leadership on student achievement, which concluded that although leadership has a strong and significant effect on teachers' classroom practices, leadership "fails to explain any of the variation in student achievement gains" (Leithwood & Jantzi, 2006, p. 223). Likewise, Witziers, Bosker, and Krüger's (2003) found that "not more than 1% of the variation in student achievement is associated with differences in educational leadership" (p. 415). However, Marzano (2007) indicates that studies conducted in the United States have actually found strong correlations between a principal's leadership and student achievement.

Quality of Instruction. Creemers's model of school effectiveness (Creemers & Kyriakidēs, 2007) defines quality of instruction as a function of three factors: curriculum (e.g., goals, content, organization, and evaluation), grouping procedures (e.g., cooperative

learning versus ability grouping), and teacher behavior (e.g., clarity of presentation, goal setting, and content emphasis). Other authors (Scheerens, 1990, 1997; Stringfield & Slavin, 1992) also include in this category of variables the constructs of opportunity to learn (Scheerens, 1997) and time on task (Scheerens, 1990), to which I will refer in more detail in the next section. Bolhuis (2003) also emphasizes the role of reinforcement, evaluation, feedback, and monitoring student progress as components of quality of instruction.

Opportunity to Learn and Time on Task. There is wide agreement among researchers that the amount of time spent on instruction is positively related to student achievement (Lee & Croninger, 1994; Scheerens, 1991, 1997; Teddlie & Reynolds, 2007). Opportunity to learn, defined as the amount of time allowed for learning (Scheerens, 1997), and time on task, which is the actual time effectively spent on learning activities (Scheerens, 1990) have often been considered in school effectiveness research. Although researchers measure time-related variables differently, measures of opportunity to learn and time on task often relate to teacher absenteeism, student absenteeism, duration of the school day, school week and year, time spent on homework assignments, content coverage, exposure, and emphasis, among others (Scheerens, 1990; Lee & Croninger, 1994; Wang, 2010). For example, teacher and student absenteeism have been found to be negatively related to student achievement (Lee & Croninger, 1994). Teddlie and colleagues' qualitative study (1989) indicate that effective use of time is one of the most salient characteristics of effective schools, while in ineffective schools "classes typically began 15 minutes later than scheduled. Children returned from recess at their leisure. A 15-minute scheduled recess often lasted 30 minutes." (Teddlie, Kirby, & Stringfield, 1989).

Teacher Characteristics. Teacher characteristics are usually found in school effectiveness models as aggregated variables at the school level, measured as teacher education, teacher experience, and teacher salary (Teddlie & Reynolds, 2000). In some multilevel studies teachers are used as the group-level criteria, in which teacher-level factors usually refer to a more broad set of teacher factors such as teacher attitudes and behaviors, instructional styles, instructional strategies, and classroom management (Creemers & Kyriakides, 2010). In fact, the study of teaching effects eventually became a more specific field of study within school effectiveness and improvement (Teddlie & Stringfield, 2007), usually referred to as teaching effectiveness research (TER) (Teddlie & Reynolds, 2000) or educational effectiveness research (EER) (Creemers & Kyriakidēs, 2007). This area of research has focused on measures of observable teaching behaviors that are directly associated with student achievement rather than teacher characteristics that might explain such behavior (Creemers & Kyriakides, 2010; Teddlie & Reynolds, 2007).

Parental Involvement. The literature on school effectiveness has generally found a positive impact of some types of parental involvement on student achievement, although some studies in this area have failed to find such an impact (Teddlie & Reynolds, 2007). Parental involvement in the form of parental awareness of school goals and student responsibilities, parental participation in school activities (Davis & Thomas, 1989, Teddlie & Reynolds, 2000), parental homework supervision (Fan & Chen, 2001; Lee & Croninger, 1994), and parental aspirations and expectations for students' educational achievement (Fan & Chen, 2001) have the most impact on student achievement. Marzano (2007) provides three definitions of parental involvement that are usually used in school effectiveness research: 1) communication, which refers to the

extent to which a school has developed reciprocal means of information and communication with parents; 2) participation, which refers to the degree to which parents are involved in school activities; and 3) governance, which refers to the extent to which parents are involved in the decision making process of the school.

Field-level Studies

Field-level research focuses on the macro-level factors related to the institutions, professions, and technologies of admissions with the purpose of investigating the mutual influence between student behaviors and institutional actions (McDonough & Fann, 2007). As such, this section includes a discussion of some issues related to the widespread use of standardized tests in college admissions and the reciprocal impact of this use on students and institutions.

Test Coaching. Given the importance of standardized tests in gaining admission to college, the test preparation industry has been steadily increasing in size and popularity (Forest & Kinser, 2002). Many studies have long focused on the effects of test coaching on students' performance on standardized tests, particularly the effects of test preparation for the SAT and ACT (Allalouf & Ben-Shakhar, 1998). Although different definitions of test coaching can be found in these studies (Anastasi, 1981; Becker, 1990; Messick, 1982; Zwick, 2002), most of them agree that coaching entails activities undertaken by students with the specific purpose of improving their performance on standardized tests. Messick (1982) broadly defines coaching as "any intervention procedure specifically undertaken to improve test scores, whether by improving the skills measured by the test or by improving the skills for taking the test, or both" (p. 70). These activities may range from free-of-charge courses to expensive private tutoring (Zwick, 2002), and may last for many weeks or just a few hours (Becker, 1990). Although there is agreement among

researchers that coaching does have a positive impact on students' test scores (Briggs, 2004; Kenny & Faunce, 2004; Powers & Rock, 1999), the size of the effects and what constitutes a large (or a small) effect of test coaching on individual performance on standardized tests is still a matter of dispute. According to Becker (1990), who conducted a review of 23 studies on coaching for the SAT, the reported effect size of coaching varies depending on the study design and on the duration of the coaching interventions considered. Also, Powers & Rock (1999) found differential effects of test coaching on examinee subgroups. For example, these authors found that initially low-scoring test-takers enjoy slightly larger score gains from coaching than their higher-scoring counterparts. In addition, there is disagreement as to whether the effects of coaching are large enough to make an actual difference in applicants' chances of gaining admission to a particular institution (Forest & Kinser, 2002).

Other controversies concerning test coaching have also been discussed in the literature. One of the main issues is that, given the positive impact of coaching on test scores found in the literature, and because most commercial coaching schools are more likely to be accessible to more affluent test-takers (Buchmann, Condro, & Roscigno, 2010), the fairness and validity of standardized tests could be challenged (Zwick, 2002; Briggs, 2004). And while testing companies claim that coaching has very little effect on scores, commercial coaching schools assert that they can produce large score gains (Zwick, 2002).

Test Fairness and Bias. Test bias has been suggested as a possible explanation for standardized test score gaps between students of different gender, race, or social class (Forest & Kinser, 2002; Hossler & Kalsbeek, 1999). The literature related to test bias is very broad and deals with diverse issues such as equal learning opportunities and access

to testing, cultural load of item content, and the unfair influence of test-takers'

background characteristics on test scores (Janesick, 2001; McNamara & Roever, 2006;

Valencia & Suzuki, 2000). In the context of college admissions tests, the literature mostly

focuses on bias that relates to the concept of predictive validity. According to Zwick,

(2002), "the validity of admissions tests as a selection tool for higher education

institutions is judged largely by the degree to which test scores can predict later grades"

(p.79). A recent report from the College Board (Mattern et al., 2008) showed that the

SAT underpredicts college GPA for females (residuals ranging from 0.10 to 0.17for the

three sections and the combined SAT), while males' performance is overpredicted with

mean standardized (mean standardized residuals ranging from -0.11 to -0.20). In regards

to race, minority students' college GPA is overpredicted, while the college GPA of white

students is underpredicted. For best language, the results of this same report showed that

the performance of students whose best language is English is accurately predicted, while

the performance of students whose best language is not English is underpredicted by the

reading and writing sections of the SAT (mean standardized residuals of 0.40 and 0.37,

respectively), but not by the math section, which accurately predicts performance for

these students. In consonance with these results, a report by the National Association for

College Admission Counseling (NACAC, 2008) and Zwick (2002) recognizes that

admission tests scores overpredict college GPA for some minority students and

underpredict college GPA for some female students.

However, other researchers have found that the prediction validity of the SAT for

minority students widely varies across institutions depending on the racial composition of

the student body, and that the SAT's prediction validity is usually better for majority

students (Fleming, 2002; Fleming & García, 1998; Hoffmann & Lowitzki, 2005, Temp,

1971). For example, Fleming and García (1998) and Fleming (2002) found that the predictive validity of the SAT for freshman males was significantly higher in predominantly black schools. Also, Fleming and Morning (1998) found that SAT scores may not predict grades as consistently among minority students when students' adjustment to college is poor, suggesting that academic performance does not depend only on academic preparedness, but also on the institutional environment and its impact on students' adjustment to college, an explanation entirely consistent with most models of student retention (Astin, 1997; Pascarella & Terenzini, 2005; Tinto, 1994).

Test-Optional Admissions. Because of the claims of the potential bias of standardized tests against minority, female, and low-income students, a growing number of institutions, especially among smaller liberal arts colleges, are choosing to make admissions tests optional in their entrance requirements (Esphensade & Chung, 2011; Hossler & Kalsbeek, 1999). For the same reason, some states (California, Texas, and Florida) have considered completely eliminating the SAT as a requirement for college admissions (Freedle, 2008). Moreover, a commission of the National Association for College Admission Counseling (NACAC, 2008) has encouraged colleges and universities to drop college admissions tests as an admission requirement to institutions able to make appropriate admissions decisions without admissions test scores, and to those institutions in which the predictive validity of the test regarding first-year students' performance is low. Because of this, there is a small but growing body of research (Esphensade & Chung, 2011; Hiss & Neupane, 2004; Robinson & Monks, 2005; Long, Sáenz, & Tienda, 2010; Rooney & Schaeffer, 1998) focused on alternative methods and factors to be considered in college admissions and their potential effect on the racial, socioeconomic, and academic profiles of admitted students. Most of this research refers to the use of high

school GPA and class ranking to predict students' success in college. These studies have found that these alternative methods to select students have resulted in campuses with a more diverse student body.

Chapter 3: Methodology

Research Questions

The purpose of this study is to identify the main individual characteristics that impact performance on college admissions tests among Chilean high school graduates. Also, this study aims to ascertain the extent to which Chilean high schools affect students' performance on college admissions tests. Consequently, the research questions guiding this study are as follows:

1. To what extent does students' performance on college admissions tests vary across Chilean high schools?

2. Which individual student characteristics predict performance on college admissions tests among Chilean high school graduates?

3. To what extent does the relationship between students' individual characteristics and their performance on college admissions tests vary across schools?

4. Which school characteristics explain the variability of students' performance on college admissions tests between schools?

5. To what extent do school characteristics influence the relationship between students' characteristics and their performance on admissions tests?

Hypotheses

Research Question 1. Because the Chilean system of education is highly unequal and segregated (OECD & The World Bank, 2009), I hypothesized that student performance would vary significantly across Chilean schools. Given the significant inequality present in the Chilean educational system, it is reasonable to expect that the proportion of variance in performance that lies between Chilean schools will fall in the higher range of what has been reported in prior studies of other countries. For example, a

study of student achievement conducted by the Programme for International Student Assessment (PISA) found an average ICC between math and reading tests of 52.5% in 2006 for Chilean schools, while for the United States the ICC was approximately 25% and for Norway it was 11% (OECD, 2009).

Research Question 2. Prior studies have found that in Chile there is an achievement gap in college admissions test scores mostly associated with students' gender, family income, parental education, and the type of school attended (Contreras, Corbalán, & Redondo, 2007; CTA-CRUCH, 2004; 2005; Koljatic & Silva, 2006; 2010; OECD & The World Bank, 2009). Therefore, I expect to find that females and students from lower socioeconomic backgrounds will perform more poorly on college admissions tests than their male counterparts from more advantaged socioeconomic backgrounds. I have also included in this study additional variables that capture students' high school rank and the number of siblings students' have in higher education, which I hypothesized may also have a positive impact on student performance on admissions tests. This hypothesis was informed by similar studies conducted in the United States, which found that students who have older siblings in college are encouraged and supported by those siblings on their path to college (McDonough & Fann, 2007; Tierney, Corwin, & Colyar, 2004), that for minority students having an older sibling in higher education increases their likelihood of enrolling in a postsecondary institution (Loury, 2004), and that low-income students who have siblings in higher education have higher levels of achievement (Widmer & Weiss, 2000).

Research Question 3. Lee, Bryk and Smith (1993) argue that American schools are "internally differentiating institutions," and that school effectiveness research has found that inequity in American education is not only observed between schools, but also

within the same schools due to school practices that create substantial variability in students' opportunities to learn. Consequently, I hypothesized that the relationship between individual student predictors and student performance on admissions tests may vary across schools.

Research Question 4. I assume that students' performance on college admissions tests is affected by the characteristics of the school which they attend. Based on the Chilean literature (Contreras et al., 2007; CTA-CRUCH, 2004; 2005; OECD & The World Bank, 2009; Valdivieso et al., 2006), I expect to find that school sector and the socioeconomic composition of the school will explain most of the differences between schools. Based on Lee and Croninger (1994), I also expect to find that school structure (e.g. school sector), school composition (e.g. aggregated level of income), and policies (e.g. selection of students) have an effect on student performance on admissions tests.

Research Question 5. I hypothesized that the effect of student characteristics on student performance on college admissions tests might be moderated by some school characteristics. This means that I expect to find cross-level effects, which indicate that school characteristics impact the relationship between individual predictors and performance. I also hypothesize that I will find contextual effects, which indicate that the effect of student aggregate variables impacts school means. Neither cross-level nor contextual effects have been investigated in prior research on this study's topic. Therefore, in the absence of prior evidence regarding how Chilean schools affect the relationship between students' characteristics and their performance, it is difficult to anticipate which school characteristics may have an equalizing effect on student performance.

Sources of Data

This study draws from two main Chilean datasets: Prueba de Selección Universitaria (PSU) and Sistema de Medición de la Calidad de la Educación (SIMCE). Both datasets contain census-like data; i.e., these tests are applied in all schools nationwide.

Admissions Test (PSU) Dataset. This dataset, hereafter called the PSU dataset (PSU stands for Prueba de Selección Universitaria, meaning college admissions tests) contains information about all Chilean high school graduates (approximately 249,000 applicants) who registered to take the college admissions tests in Chile in 2009. The Department of Evaluation, Measurement and Educational Records (DEMRE) authorized the use of the PSU dataset for this study following the submission of a formal request for access (see Appendix B for written consent). DEMRE is the official Chilean national agency responsible for the construction and administration of the admissions tests in Chile. This dataset is composed of four files containing: 1) school information, 2) socioeconomic information about registered students, 3) students' test scores and other academic information, and 4) students' applications and admission information, respectively.

Prior Achievement (SIMCE) Dataset. SIMCE is the Department of Learning Outcomes Assessment of the Chilean Ministry of Education. SIMCE standardized tests assess the achievement of fundamental objectives and minimum compulsory contents of the current national curriculum in math, language, natural sciences, and social sciences. These tests are administered nationwide once a year to fourth graders, and every other year to eighth and tenth graders. Therefore, the data correspond to the entire population of fourth, eighth, and tenth graders.

I was granted access to restricted SIMCE files of students, which contain information about approximately 245,000 tenth graders who took the SIMCE math and language tests in 2006, distributed across approximately 2,500 schools (see Appendix B for written consent).

Sample

The study focused only on students who graduated from high school in 2009. Several reasons guided my decision to focus on this particular group of students. First, students who graduated before 2009 may have taken the test once or many times before. This could happen because students who did not get admitted to the major and institution of their preference may want to retake the test the next year. Also, students who want to change majors are required to take admissions tests and go through the admission process all over again. Students who have taken the test more than once would be more likely to obtain higher scores due to repetition (Zwick, 2002). Also, students who graduated before 2009 may have spent some time in a private test preparation school after graduating from high school, or they may have even attended college for awhile. These types of academic experiences have been found to increase students' performance on college admissions tests (Zwick, 2002; Briggs, 2004). Moreover, applicants who graduated before 2009 may have spent a long period outside academia. In any of these cases, the predictors of performance on admissions tests of students who graduated before 2009 are likely to be different from those affecting the performance of students who recently graduated from high school.

I must also point out that my study focused only on students in college-track schools. The reasons that compelled me to exclude vocational students from the study are twofold. First, because students attending vocational schools are exposed to a different

curriculum that does not prepare them for admissions tests, a comparison of the two groups of students would be inappropriate. Additionally, there is a more practical reason to exclude vocational students from the sample. A school's curricular focus (college-track, vocational, or both curricular offerings) is an individual characteristic in the dataset, which means the differences between the two types of students have to be analyzed at the within-school level. Unfortunately, in the dataset there are too few schools (less than 300 out of 1887) that have both curricular emphases (college-track and vocational) that would allow me to conduct such analysis.

Constructs and Measures

This section reports measures for each of the constructs used for assessing individual factors (level-1) and school factors (level-2). In so doing, I discussed the rationale I followed in choosing the measures and the re-codifications I did before performing the statistical analysis. Table 1 provides summary statistics for the corresponding measures across the two levels of analysis (e.g., the student and the school).

Outcome Variable

Student Performance on College Admissions Tests. This is the outcome variable of the model and it is measured as students' mean score on the verbal and math sections of the test. The admissions test scores range from a minimum of 201.5 points to a maximum of 846.0 points; the average test score is 528.7 points with a standard deviation (SD) of 102.4 points [1].

Table 2. *Summary of descriptive statistics of student and school variables.*

	Mean (SD) / Percent	Range [min; max]
Student Variables (n=106,415)		
Average Admission Test Scores	528.73 (102.4)	[201.49; 846.0]
High School GPA	5.65 (0.49)	[4.0; 7.0]
Gender		
Male	45.0	
Female	55.0	
Age		
Born in 1990 or before	10.9	
Born in 1991	58.1	
Born in 1992 or after	31.0	
Family Income		
Low-income	60.0	
Middle-income	16.0	
High-income	24.0	
Siblings in Higher Education	31.2	
School Variables (N=1,887)		
10th Graders Math Average Test Score	265.7 (44.9)	[176; 365]
10th Graders Reading Average Test Score	266.7 (31.6)	[197; 337]
11th Graders English Average Test Score	107.8 (23.3)	[69; 178]
College Admissions Average Test Score	509.9 (78.8)	[297; 723]
Percent of students who took college admissions tests	86.7 (18.3)	[6; 100]
School Size	739.3 (516.2)	[5; 4,436]
Class Size	29.1 (7.8)	[1; 45]
School Sector		
Private	19.2	
Subsidized private	55.5	
Public	25.3	
School Socioeconomic Group		
Low-income	30.9	
Middle-income	26.1	
High-income	43.0	
Tuition-free	27.4	
Receives Preferential State Subsidy	33.7	
Selective (entrance examination)	30.1	

Student-Level Variables

Socioeconomic Status. Usually, there are three measures associated with student

socioeconomic status in the literature: parental income, parental education, and parental

occupation (Sirin, 2005). However, the variables related to parental education and

occupational situation available in the PSU dataset had inconsistent values with respect to

the predefined categories of the variables. In other words, the coding of these variables did not match the actual values in the dataset. Because of this problem, I decided not to include these individual-based SES measures in the analysis. Therefore, this study will rely only on family income as a proxy of student socioeconomic status at the individual level. Family income is originally included in the PSU dataset as a categorical variable of twelve income brackets, which I recoded into fewer categories (low-income, 60%; middle-income, 16%; and high-income, 24%) for the purpose of simplifying the analysis.

Additionally, I included a dummy variable signifying whether the student had older sibling(s) who were attending or had attended college. Thirty-one percent of the subjects in the sample reported having older siblings who attended college. In the United States, researchers have found that having an older sibling(s) who attended college has a significant effect on students' likelihood to attend college (Loury, 2004; Widmer & Weiss, 2000).

Academic Achievement. The college choice literature regards academic achievement as a product of academic preparation. This literature also reports a positive association between academic achievement and college enrollment (Cabrera & La Nasa, 2000; Perna, 2004; Terenzini, Cabrera & Bernal, 2001). I measured academic achievement using high school GPA. In 2009, the average high school GPA was 5.65 with a standard deviation of 0.49 (see table 1). In model testing, I centered GPA by standardizing it (mean = 0 and SD = 1), to facilitate the interpretation of its effect on students' performance on admissions tests. Additionally, I included students' high school class ranking (how a student's GPA compares to the GPAs of other students in her class) as a dummy coded variable (top ten percent = 1, not in top ten percent = 0).

Demographics. Chilean studies have documented that females typically score lower than males (CTA-CRUCH, 2004; 2005; OECD and The World Bank, 2009) on the admissions test. Consequently, I incorporated gender via a dummy variable whereby males were coded as 0 and females as 1. My sample is predominately female (55%). I also included age as appraised by a three-category variable (born in 1990 or before, 10.9%; born in 1991, 58.1%; born in 1992 or after, 31.0%).

School-Level Characteristics

School Structure. This type of variable usually refers to inherent characteristics of the school that relate to resources, control, and location, which have been reported to be determinants of student performance (Kaplan, 2004; Ma, Ma, & Bradley, 2008). In this study, the variables included in this category were school sector (private, 19.2%; subsidized private, 55.5%; public, 25.3%), whether the school charges for tuition (yes, 27.4%; no, 72.6%), and whether the school receives additional preferential subsidies from the Chilean state (yes, 33.7%; no, 67.3%)

School Composition. This construct usually refers to the social milieu of the school, defined as the background characteristics of the student body, the teachers, and staff within the school (Stewart, 2008). This is typically measured by the ethnicity, socioeconomic status, and gender of students. I measured this construct using an index of socioeconomic status of the school created by the National Department of Learning Outcomes Assessment (SIMCE). This variable[2] was originally a five-category variable, which I recoded into three categories to facilitate analysis (low-income, 30.9%; middle-income, 26.1%; high-income, 43.0%). Also in this category of compositional variables, I included the proportion of female students, average school test score on tenth grade achievement tests (math, reading, and English), and average GPA of school seniors.

School Practices and Policies. Although school composition and structure establish the context in which student learning occurs, research suggests that a school's practices and policies, which shape the way in which schools decide to approach learning and instruction, really determine student performance (Lee & Croninger, 1997). In Chile, a common policy among schools that may have an impact on student performance ~~in~~ on college admissions tests is the administration of an entrance examination for admission purposes. Consequently, I incorporated a dummy variable signifying whether a school administered an entrance examination. Approximately 30% of the participating schools reported administering an entrance exam. I also included another variable to capture the percentage of students who take admissions tests (Mean 86.7, SD 18.3). This measure is a good proxy of what McClafferty, McDonough and Nunez (2002) define as college-going culture within a school.

Descriptive Relationships among Variables

Correlations. I obtained correlations for student and school variables using Lisrel 8.0. This software allows for the obtainment of more accurate estimations of correlations when some of the variables are categorical or binary (polychoric correlations).

Table 3. *Correlations among variables of the student dataset*

Student Variable	1	2	3	4	5	6	7
1. High school GPA	1.000						
2. Class ranking	0.855	1.000					
3. Family income	0.249	0.042	1.000				
4. Age	0.198	0.184	-0.028	1.000			
5. Gender	0.125	0.135	-0.108	0.079	1.000		
6. Having siblings in HE	0.067	0.014	0.258	0.023	-0.018	1.000	
7. Admissions Test Scores	0.637	0.444	0.516	0.148	-0.145	0.150	1.000

Table 3 shows the correlations among the student variables considered for this study. The outcome variable (admissions test scores) is highly to moderately correlated to students' GPA, class ranking, and family income, while it is slightly correlated to age, gender, and having siblings in higher education.

Table 4 displays the correlations among school variables, which are relatively higher than those among student variables. First, there is a high degree of correlation between school sector and socioeconomic status (-0.877). Second, there is also a strong association between the amount of tuition charged, school sector (-0.893), and socioeconomic status (0.881). The correlation is also very high among the three sections of 10th graders' tests of achievement (0.976, 0.856, and 0.860 respectively), and between performance in these tests and school sector (-0.725, -0.719, and -0.837 respectively), socioeconomic status (-0.725, -0.719, and -0.837 respectively), and tuition (0.713, 0.702, 0.802).

Distribution of Students across Schools by Sector. Table 5 shows how students are distributed across school sectors depending on their income, gender, age, and whether they have siblings in higher education. In the cases where the percentage of students within sectors is larger than the average distribution of students in the sample, students in that category are overrepresented, and in the cases where the average percentage is larger in the sample than within a certain category, students are underrepresented. In terms of income, it is quite evident that school sectors are highly segregated. High-income students are overrepresented in private schools (80.6%), while low-income students are overrepresented in public schools (83.2%). Also, students of different gender are evenly distributed in subsidized private and public schools, while in private schools females are underrepresented (49.6%). Older students in the cohort under study are overrepresented

in public schools (74%), and younger students of the same cohort are underrepresented in

private schools (20.8%). Students who have siblings in higher education are

overrepresented in private schools (40.7%) and slightly underrepresented in public

schools (26%).

Table 4. *Correlations among school variables*

School Variable	1	2	3	4	5	6	7
1. Preferential subsidy	1.000						
2. Sector	0.427	1.000					
3. Socioeconomic Status	-0.486	-0.877	1.000				
4. Average class size	0.224	0.311	-0.126	1.000			
5. School size	0.165	0.027	0.094	0.565	1.000		
6. Entrance examination	-0.420	-0.477	0.508	-0.039	0.071	1.000	
7. Tuition	-0.506	-0.893	0.881	-0.166	0.018	0.471	1.00
8. Prop. of students taking tests	-0.117	-0.571	0.717	0.120	0.129	0.356	0.578
9. 10th graders reading test	-0.374	-0.725	0.872	0.092	0.239	0.523	0.713
10. 10th graders math test	-0.398	-0.719	0.859	0.081	0.250	0.527	0.702
11. 10th graders English test	-0.512	-0.837	0.932	-0.166	0.108	0.512	0.802
12. Average school GPA	-0.284	-0.422	0.502	-0.033	0.132	0.342	0.331
13. Prop. of females	0.069	0.081	-0.042	0.085	-0.007	-0.081	-0.052

	8	9	10	11	12	13	
8. Prop. of students taking tests	1.000						
9. 10th graders reading test	0.649	1.000					
10. 10th graders math test	0.620	0.976	1.000				
11. 10th graders English test	0.545	0.856	0.860	1.000			
12. Average school GPA	0.270	0.629	0.638	0.573	1.000		
13. Prop. of females	0.014	0.049	0.008	-0.045	0.112	1.000	

Table 5. *Student distribution across school sectors by income level*

School Sector	Student Characteristics		
	Family income		
	Low-income	*Middle-income*	*High-income*
Private	8.4%	11.1%	80.6%
Subsidized private	60.6%	21.2%	18.1%
Public	83.2%	10.6%	6.1%
Total	60.0%	16.1%	24.0%
	Gender		
	Male		*Female*
Private	50.4%		49.6%
Subsidized private	44.0%		56.0%
Public	43.8%		56.2%
Total	45.0%		55.0%
	Age		
	Born in 1990 or before	*Born in 1991*	*Born in 1992 or after*
Private	9.5%	69.7%	20.8%
Subsidized private	9.6%	57.0%	33.4%
Public	13.5%	54.4%	32.1%
Total	10.9%	58.1%	31.0%
	Siblings in Higher Education		
	No		*Yes*
Private	59.3%		40.7%
Subsidized private	68.3%		31.7%
Public	74.0%		26.0%
Total	68.8%		31.2%

Data Preparation

I examined the data prior to model testing to judge the extent to which it met important assumptions needed when using regression-based methods. To verify the assumption of normality, I combed the data for potential outliers and skewness. I also examined the potential presence of multicollinearity among variables. Finally, I examined the amount and patterns of missing data.

Search for Outliers. Two methods were used to search for outliers in the data: 1) looking at z-scores with values higher than 3 or lower -3 and 2) obtaining the Mahalanobis Distance (MD) as recommended by Raykov and Marcoulides (2008).

Student Dataset. In the student dataset, none of the continuous variables showed

z-scored values outside the outlier range [3,-3]. When using large datasets like the student

dataset in this study, the Mahalanobis Distance follows approximately a χ^2 distribution

with degrees of freedom being the number of variables considered (Raykov &

Marcoulides, 2008). Given this property of the MD statistic, an observation is considered

a multivariate outlier if the correspondent MD value for that observation is larger than the

critical value at a particular level of significance of the χ^2 distribution (Raykov &

Marcoulides, 2008). In the case of the student dataset, using the seven variables of

interest, the maximum value of the MD was 19.44. Using a χ^2 table, I found that the

critical value at $\alpha = 0.001$ and $df = 6$ is 22.46. Therefore, I could comfortably conclude

there were no outliers in the student dataset.

School Dataset. When analyzing the school dataset I found that four variables

(class size, school size, percentage of students who took admissions tests, and average

school GPA) had z-score values outside the [-3, 3] range (see Table 6). The MD critical

value (34.53, $\alpha = 0.001$ and $df = 13$) indicated that 32 schools were possible outliers in

the school dataset.

Table 6. *Z-score value range for school variables.*

School Variable	Minimum	Maximum
Class Size	-3.63	2.05
School Size	-1.42	7.16
Percentage of Students Who Took College Admissions Test	-4.42	0.71
Average school GPA	-5.25	3.97

Although the analyses suggest the existence of many outliers in the school

dataset, I decided to keep those cases for my model testing. My reasons for doing so

were: 1) eliminating such a large number of schools from the dataset would result in a

large loss of information, as with every school discarded from the dataset, a much higher number of students are also discarded in the process, 2) the cases in question appeared to reflect legitimate variability in the studied population, after thoroughly checking for coding or typographical errors that might have caused extreme values for the identified cases, and 3) preliminary multilevel analyses showed no significant changes in the magnitude or direction of the effects of school- and student-level variables on the outcome variable when comparing the results both including and excluding outliers.

In addition to the MD and outlier analyses, I examined the presence of kurtosis and skewedness as well as the distribution of the variables using Q-Q plots. A moderately conservative rule to follow in order to assess normality is that a variable is considered not normally distributed if the skewness and kurtosis indices exceed ±2 in magnitude (Finney & DiStefano, 2006). Table 7 shows the values of kurtosis and skewness for each continuous variable in the student and school dataset.

Also, normality can be graphically assessed by looking at histograms and quantile-quantile (Q-Q) plots. The Q-Q plots compare ordered values of a variable with quantiles of the theoretical normal distribution. If two distributions match, the points on the plot should form a linear pattern passing through the origin with a unit slope (Raykov & Marcoulides, 2008). Figure 4 and Figure 5 show the Q-Q plots and histograms for each continuous variable in the student and school datasets, respectively.

An examination of those Q-Q plots, frequency distribution and skewness revealed that only one variable, school size, was highly skewed. Therefore, and with the aim of simplifying interpretation, I transformed this variable from a continuous to categorical (small, 25.7%; medium, 52.4%; large, 21.9%).

Table 7. *Skewness coefficients of student and school continuous variables.*

	Skewness
Student Variables	
Admission mean test score	0.010
High School GPA	0.290
School Variables	
10th Graders Average Score on English Test	0.811
10th Graders Average Score on Math Test	0.168
10th Graders Average Score on Reading Test	0.043
College Admissions Average Test Score	0.687
Percent of students who took college admissions tests	-0.821
Class Size	-0.549
School Size	2.006
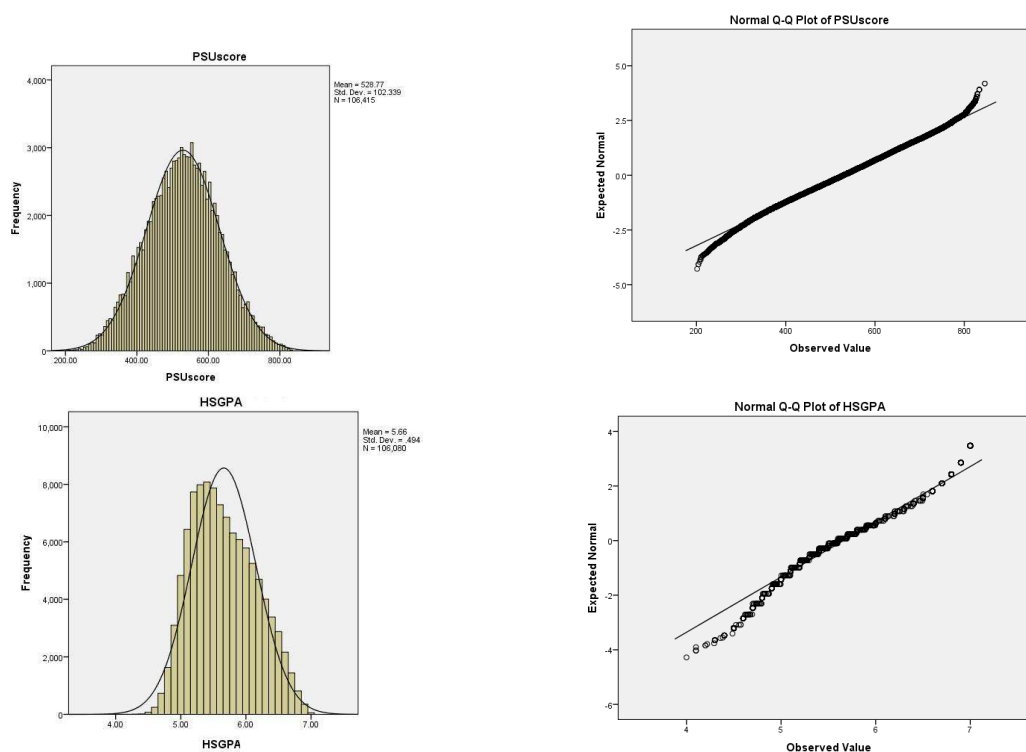
Figure 4. Histograms and Q-Q plots of continuous variables.
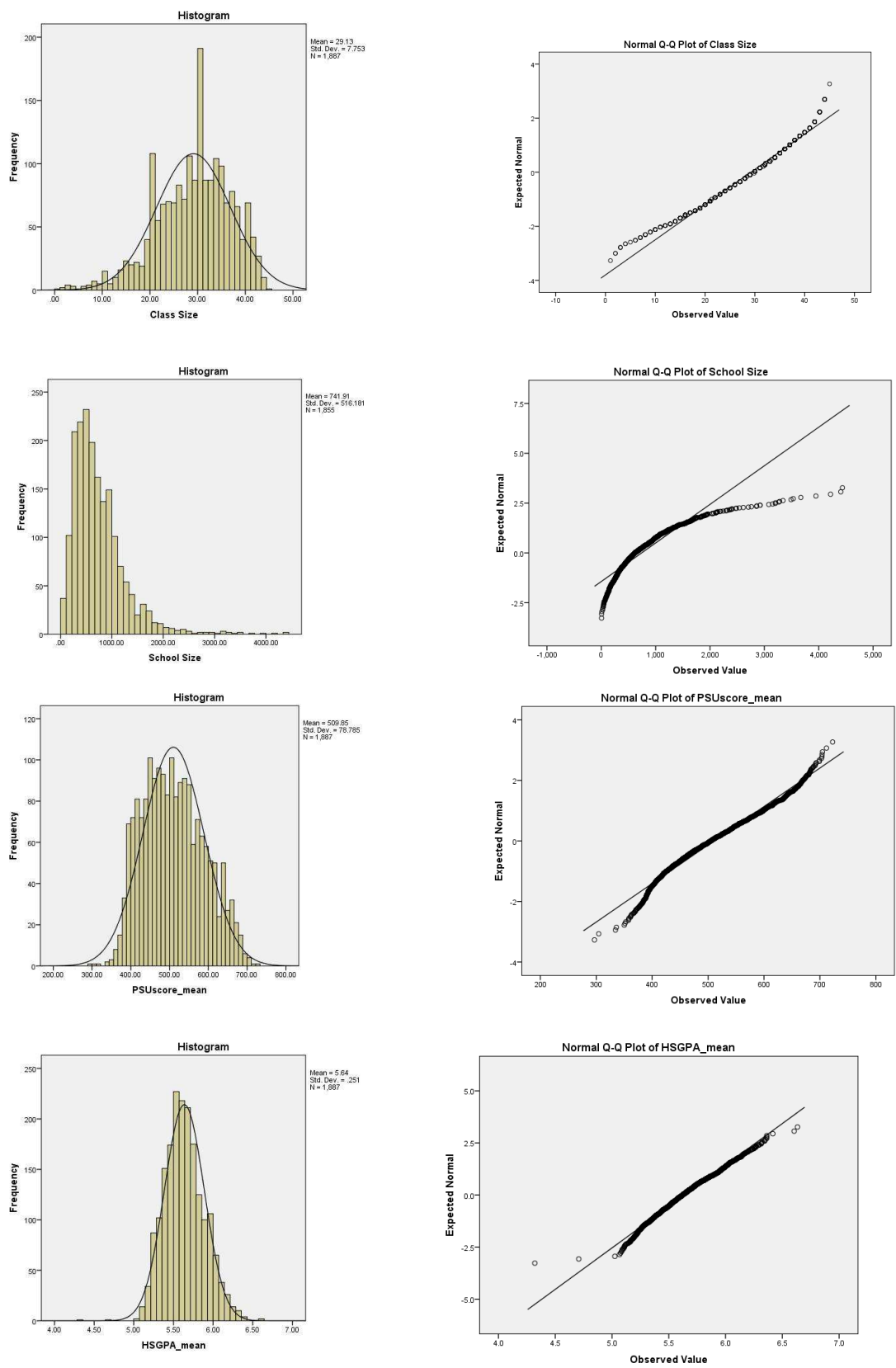
Figure 5. Histogram and Q-Q plot of some school continuous variables.

Detecting Multicollinearity. Multicollinearity exists between variables that are not independent of one another. The existence of multicollinearity among predictors might yield models with high reliability coefficients but no statistically significant effects, parameter estimates of implausible sign or magnitude, and/or large standard errors (O'Brien, 2007). In order to avoid these problems, the variance inflation factor (VIF) was used as a criterion to assess whether variables included in this study were multicollinear.

The VIF shows how much of the variance in the model has been inflated due to a lack of independence between variables, i.e. how much of the estimated variance of an estimated parameter is increased above what it would be if the variables were perfectly independent of one another (Freund, Mohr & Wilson, 2010; O'Brien, 2007). The larger the VIF, the higher the multicollinearity between variables. There is no agreement between researchers regarding VIF value that can be considered acceptable. It has been suggested a wide range of acceptable value of the VIF, ranging from of 4 to 10 (O'Brien, 2007). However, most authors in the social sciences recommend a threshold of 10 (e.g. Cohen, 2003; Freund, Mohr & Wilson, 2010), which is the criterion for this study.

I regressed each independent variable using the others as predictors to compute the VIF values. As shown in Table 8, the student dataset did not show evidence of multicollinearity, as the VIF values are all approximately 1. On the contrary, the school variables related to 10th graders' achievement showed a high degree of collinearity, with some values higher than 20. In order to address these multicollinearity problems, the literature suggests two possible approaches: 1) creating composites of appropriate subsets of variables when possible, or 2) dropping one or more problematic variables from the analyses (Freund, Mohr & Wilson, 2010; Raykov & Marcoulides, 2008).

Table 8. *Vector inflation factor (VIF) values of student and school characteristics.*

	VIF
Student Variables	
High School GPA	1.111
Family Income Category	1.105
Age	1.038
Siblings in higher education	1.031
Gender	1.021
School Variables	
10th Graders Average Score on Reading Test	24.30
10th Graders Average Score on Math Test	22.95
Socioeconomic Status Group	7.02
10th Graders Average Score on English Test	6.77
School tuition	5.19
School sector	3.99
Percentage of Students Who Took College Admissions Test	2.18
Class Size	2.09
School Size	1.65
School Receives Preferential State Subsidy	1.33
Selective schools	1.23

Creating Composites. The variables related to prior achievement showed the highest VIF values. Therefore, and because the correlation obtained between these three variables are highly correlated to each other (see Table 4), I deemed it appropriate to build a composite measure of prior achievement out of the scores of 10th graders in math, reading, and English. To do so, I conducted a principal component analysis (PCA). After replacing the 10th graders; achievement variables with the composite variable obtained, I computed VIF values once more to assess whether the multicollinearity persisted. The new VIF values are still somewhat high (11 for school tuition, 7.5 for socioeconomic group, and 5 for the newly created composite). It seemed that although the new prior achievement factor helped to decrease the degree of multicollinearity, there was still room for improvement.

Consequently, and because some categorical school variables may be affecting the stability of the fixed effects of other predictors on the outcome variable, I conducted an exploratory ordinal factor analysis using LISREL 8.8. I hoped to uncover possible underlying structural associations among school characteristics and examine whether it was feasible to create another composite of ordinal variables in the school sample. The variables considered for this exploratory analysis were: school sector, school size, school tuition, selectivity, proportion of students who took the admissions test (categorized), and socioeconomic group. However, because the bivariate normality assumption cannot be hold for these variables, I decided it was not appropriate to build a composite out of these variables[3].

Dropping Problematic Variables. The results of this analysis also showed that school sector and school SES were highly correlated. Additionally, prior achievement (the composite of 10th graders' achievement tests) was highly correlated with school sector, school SES, and with the outcome variable. For that reason, I decided to exclude this composite from the study. Regarding the correlation between school sector and school SES, I decided to keep these variables and reassess in further analyses if their collinearity was still problematic.

Missing Data Analysis. This analysis looked at the amount and patterns of missing data to determine an appropriate strategy for handling missing data.

Amount of Missing Data. First, I examined the amount of missing data, i.e. the variables for which there is a large proportion of missing data and the number of schools and students for whom there is no available data for the variables under study. Table 9 shows the amount of missing data for school and student variables. Only variables with more than 0.1% of data missing were included in the tables. The proportion of missing

data across the 12 variables under consideration is rather small, ranging from 0.3% to

6.5%.

Table 9. *Amount of missing data for school and student variables.*

Variables	Valid N	Missing	
		Count	Percent
School Variable (N=1,887)			
Socioeconomic Status Group	1,820	67	3.6
School Tuition	1,850	37	2.0
11th Graders Average Score on English Test	1,856	31	1.6
Proportion of students who take admissions tests	1,854	33	1.7
School Receives Preferential State Subsidy	1,861	26	1.4
School Size	1,865	22	1.2
Class Size	1,865	22	1.2
10th Graders Average Score on Math Test	1,881	6	0.3
10th Graders Average Score on Reading Test	1,881	6	0.3
Listwise	1,765	122	6.5
Student Variables (n=106,415)			
Admissions Test Score	106,022	450	0.4
High School GPA	106,140	335	0.3
Listwise	105,641	774	0.7

Patterns of Missing Data. I subsequently turned my attention to patterns of

missing data, i.e. the extent to which there is a consistent way in which data are missing

(McKnight et al., 2007). The literature often classifies these patterns into three categories:

missing completely at random (MCAR), missing at random (MAR), and not missing at

random (NMAR) (Croninger & Douglas, 2005; McKnight et al., 2007). To test whether

data is MCAR, Little's hypothesis tests were conducted at the school and student level

(school dataset: $\chi^2 = 69.625$, $df = 43$, *p-value* $=0.006$, student dataset: $\chi^2 = 480.874$,

$df = 2$, *p-value* < 0.001). The null hypothesis for Little's MCAR test is that the data are

missing completely at random. Because the significance value is less than 0.001 for

Little's tests at both school and student levels, I concluded that in the school and student

datasets data are not missing completely at random. This result is not surprising given that "MCAR is rarely found in empirical research unless it is created by design" (Raykov & Marcoulides, 2008, pp. 395).

Given the fact that data is not MCAR, and that there is no practical way to test for MAR (Raykov & Marcoulides, 2008), this study will assume that data is MAR and handle missing data accordingly by using imputation techniques based on expectation maximization (EM) algorithms. Making this assumption should not be problematic, because even if data are not MAR, previous studies have shown that imputation with expectation maximization (EM) techniques are robust against violations of the MAR condition (Raykov & Marcoulides, 2008).

Handling Missing Data. Discarding cases or variables with missing data might result in a loss of statistical power due to a smaller sample size, the possibility of getting biased estimates for parameters, or the loss of sample representativeness of the population under study (Gibson & Olejnik, 2003). To avoid these problems, and because the amount of missing data is relatively small for both datasets, I decided to singly impute variables using other variables in the model as predictors with the fully conditional specification in SPSS 20. This feature of SPSS is based on a Markov Chain Monte Carlo (MCMC) method that can be used when the pattern of missing data is arbitrary by fitting a univariate regression model using all other variables as predictors to impute values based on the estimated model (SPSS manual, 2011).

The use of single imputation in this study allowed for the use of all cases with partial data by generating possible values for missing values using expectation–maximization (EM) techniques in SPSS20. Estimates of regression weights produced by EM methods have been shown to be consistently less biased than those produced by

simple regression, listwise deletion, or pairwise deletion (Gibson & Olejnik, 2003). During the imputation process, SPSS used linear regression to estimate missing values of continuous variables, and logistic regression for categorical variables. Each model used all other variables as main effects. As a result of this process, SPSS created a complete set of data that I used in HLM7 to conduct the hierarchical linear modeling.

Conceptual Model

Based on the literature review conducted for this study, I proposed a conceptual model that incorporates the main individual and school variables found in the datasets under analysis that might have an impact on students' performance on college admissions tests.

I proposed that both individual agency and school actions have an effect on student performance. Therefore, the model has a nested-layered structure of students nested within schools. This model assumes that: 1) at the school level, students are affected by the particular contexts of their respective schools, not only by the structural school characteristics but also by the aggregated social and academic characteristics of their peers and school practices and policies, and that 2) at the individual level, socioeconomic status, academic achievement, and demographic characteristics have an impact on student performance on admissions tests. Finally, the model assumes that there are cross-level interactions, i.e. that some school characteristics and aggregates of student characteristics may influence the relationship between students' predictors and outcomes.
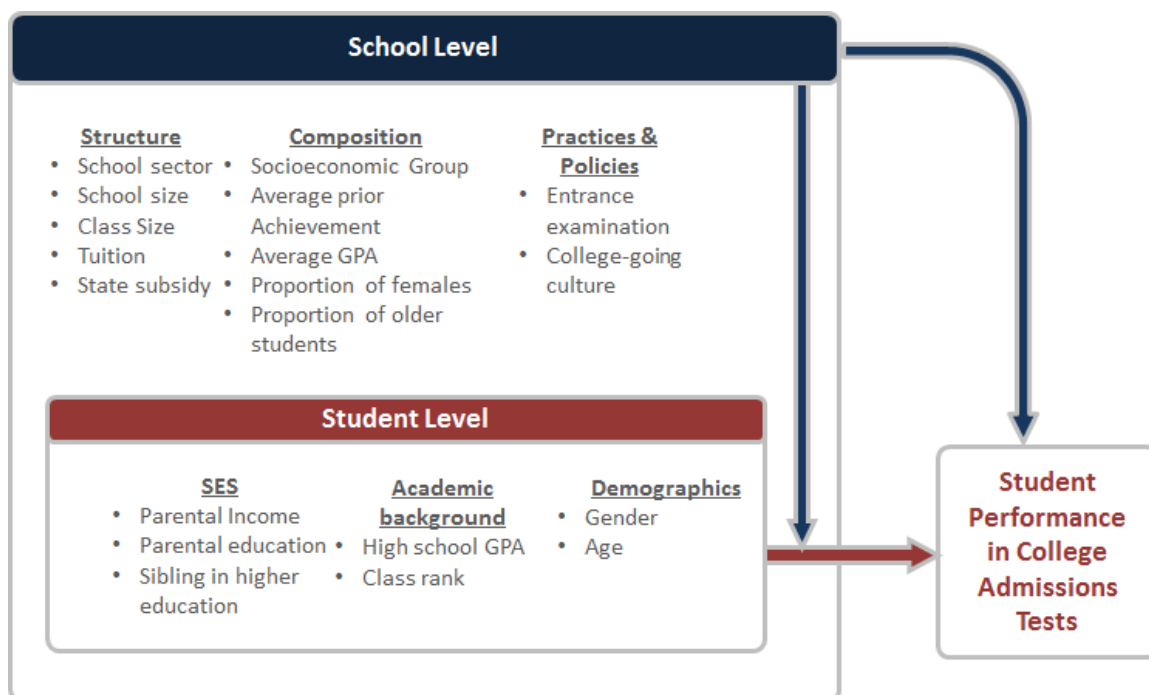
Figure 6. Conceptual model.

Analytical Approach

In answering the five research questions posed in this study, I relied on hierarchical linear modeling techniques (HLM) to obtain a multilevel model of individual and school factors that simultaneously explain the variability of students' scores on admissions tests. In doing so, it builds upon the work of previous studies, which only used descriptive and regression-based models to analyze this topic.

Two main approaches have been used in prior Chilean research on the factors affecting student performance on admissions tests. One approach has been to model test scores only at the individual level, ignoring the fact that students are grouped in schools (Contreras et al., 2007). This approach overlooks the fact that students' test scores at one particular school are likely to be correlated due to grouping (Luke, 2005; Ma, Ma, & Bradley, 2008). As a consequence, by ignoring the correlation that exists among students' performance at the same school, the researchers who conducted these studies have

incorrectly assumed that these observations were independent, violating one of the basic assumptions of parametric linear regression techniques (Hedeker & Gibbons, 1994; Luke, 2005; Ma, Ma, & Bradely, 2008).

A second approach has been to analyze data at the group level, e.g. by school sector or gender (CTA-CRUCH, 2004; 2005). In this case, the test score of a group is an aggregate of individual test scores. This approach is problematic as well for three reasons: 1) it overlooks individual differences, making it difficult to account for the effects of other individual factors, 2) the statistical power might decrease at the aggregated data, and 3) there is a possibility that the Type II error may increase (Hedeker & Gibbons, 1994).

The use of the HLM approach in this study overcomes these problems. HLM techniques allow researchers to avoid these problems because student performance on admissions tests at the individual level (the dependent variable) is modeled in terms of both student- and school-level variables "while concurrently estimating and adjusting for the amount of intraclass correlation present in the data" (Hedeker & Gibbons, 1994, p. 758). HLM also allows researchers to model data for a varying number of students within each school.

Two-Level General Model

The purpose of this study is to examine how a student's score on the admissions tests is influenced both by characteristics of the students (level-1 model) as well as characteristics of the student's school (level-2 model). Therefore, I advanced a two level model as depicted in Equations 1 and 2, which is usually referred to as an intercepts- and slopes-as-outcomes model.

$$\text{Level 1}: Y_{ij} = \beta_{0j} + \sum_{q=1}^{Q} \beta_{qj} X_{qij} + r_{ij} \qquad (1)$$

where Y_{ij} : Individual standardized admissions test score for student i in school j

N : number of students

J : number of schools

Q : number of student predictors

X_{qij} : qth student predictor of student i in school j

β_{0j} : average students' test score for school j

β_{qj} : effect of the qth student predictor on students' test scores in school j

r_{ij} : test score error for student i in school j

Level-2 model is defined by the following equation:

$$\text{Level 2}: \beta_{qj} = \gamma_{q0} + \sum_{s=1}^{S} \gamma_{qs} W_{sj} + u_{qj} \qquad (2)$$

where β_{qj} : level-1 coefficients

S : number of school predictors

Q : number of student predictors

J : number of schools

γ_{q0} : the mean of Y_{ij} for schools at the 0 value of all school level predictors

γ_{qs} : effect of the sth school predictor on the relationship between Y_{ij} and the qth

student predictor

W_{sj} : sth school predictor of school j

u_{qj} : level-2 random effects.

In the next chapter, I refer to the steps I followed to specify this model and the results it yielded, which provide answers to the five research questions posed in this study.

Notes

1.   It is important to mention that in preliminary analysis I considered and assessed in

the option of having two separate outcome variables (math and verbal test scores),

i.e. building a multivariate multilevel model that had two outcome variables.

However, because the magnitude and direction of the effects of student and

school predictors on the math and verbal sections of the test were very similar, I

decided to use the mean score of the two tests as the outcome variable.

Additionally, because the science and social sciences sections of the tests are

optional and only about 20 percent of the students took all the sections of the test,

I decided to exclude these sections from the study, so they are not included in the

calculation of the mean score.

2.   The index of socioeconomic status of the school used in this study is a variable

that was created by the National Department of Learning Outcomes Assessment

(SIMCE) using cluster analysis techniques to classify schools into five categories

based on survey data about parental level of education and family income and a

school vulnerability index provided by the National Board of Student Aid and

Scholarships (JUNAEB), an institution that provides scholarships and free-lunch

programs to schools with a high proportion of low-income students.

3. The ordinal factor analysis showed that the bivariate normal distribution

assumption could not be hold for several pairs of variables (selectivity vs. sector,

tuition vs. socioeconomic group, preferential subsidy vs. sector, preferential

subsidy vs. tuition, and preferential subsidy vs. socioeconomic group). The

violation of the bivariate normality assumption implies that the polychoric

correlations obtained may not be accurate for those pairs of variables, (Jöreskog,

2002) and therefore that a composite built out of these variables may not be a

reliable. For that reason, I decided it was not appropriate to create a composite out

of these seven variables.

Chapter 4: Results

Introduction

This chapter provides answers to the five research questions guiding this study. The first question relates to whether or not students' performances vary significantly between different schools. The second and third questions look at the individual student characteristics that predict performance on college admissions tests among Chilean high school graduates, and the extent to which the relationship between those students' individual characteristics and their performance on college admissions tests vary across schools. Finally, the fourth and fifth questions focus on the school characteristics that may influence students' performance on admissions tests and the extent to which those school characteristics impact the relationship between individual characteristics and performance.

This chapter is organized to initially provide a descriptive analysis to portray the main characteristics of schools and students included in the sample in relation to the outcome variable. Next, I briefly describe the steps followed in the specification of the model. Then, I summarize the findings of the random intercept and slopes model obtained. Finally, the last section of this chapter provides answers to each of the study's five research questions.

Descriptive Analysis

In order to investigate whether average student performance differed according to individual and school characteristics, I obtained means for the outcome variable (admissions test scores).

Students. Test score means shown in Table 10 revealed that, on average, female students scored almost 24 points lower than male students on college admissions tests.

Also, older students in the cohort (born in 1990 or before) scored lower than their

younger counterparts. The mean score was higher for students whose families have

higher incomes, with low-income students scoring much lower than high-income

students. Having older siblings in higher education was also related to higher mean

scores. Finally, higher achieving students scored higher on admissions tests than students

who have relatively lower GPAs. Students in the highest GPA decile scored, on average,

more than 150 points higher on admissions tests than students in the lowest decile.

Table 10. *Students' mean scores on college admissions tests in the year 2009*

Student Variables *(n=106,415)*	Test Score Mean (se)	Standard Deviation
All students	528.77 (0.31)	102.34
Gender		
Male	541.86 (0.48)	106.64
Female	518.08 (0.41)	102.96
Age		
Born in 1990 or before	463.12 (0.86)	93.02
Born in 1991	539.32 (0.41)	102.64
Born in 1992 or after	532.08 (0.53)	96.24
Family Income		
Low-income	495.97 (0.37)	93.48
Middle-income	541.96 (0.67)	88.22
High-income	602.11 (0.57)	91.79
Siblings in Higher Education		
Yes	546.04 (0.54)	98.02
No	520.96 (0.38)	103.29
Class Ranking (based on GPA)		
1st Decile	462.32 (0.88)	85.51
2nd Decile	478.96 (0.86)	89.16
3rd Decile	490.23 (0.86)	89.69
4th Decile	503.74 (0.89)	91.46
5th Decile	513.28 (0.90)	92.66
6th Decile	526.84 (0.89)	93.96
7th Decile	541.43 (0.90)	93.17
8th Decile	560.23 (0.89)	92.97
9th Decile	584.18 (0.88)	92.11
10th Decile	621.14 (0.90)	91.21

Schools. Table 11 shows the mean test scores for schools according to sector,

socioeconomic group (SES), size, tuition, preferential state subsidy, and selectivity. On

average, students attending private schools scored significantly higher than subsidized

private and public schools. Higher mean differences existed between schools depending

on the socioeconomic status of the students they serve.

Table 11. *Schools' average test scores*

School Variables *(n=1,887)*	Test Score Mean	Standard Deviation
All schools	509.85 (1.81)	78.79
School Sector		
Public	442.52 (2.49)	54.32
Subsidized private	507.70 (1.78)	57.77
Private	604.79 (3.25)	61.76
School Socioeconomic Group		
Low-income	429.52 (1.53)	36.95
Middle-income	496.41 (1.82)	40.34
High-income	575.85 (2.04)	57.97
School Size		
Small (<= 400 students)	489.74 (3.53)	77.63
Middle (401 – 1,000 students)	505.96 (2.48)	78.07
Large (1,000+ students)	542.68 (3.52)	71.60
Tuition-free		
Yes	444.96 (2.43)	55.20
No	534.34 (1.95)	72.20
Receives Preferential State Subsidy		
Yes	473.27 (2.35)	59.17
No	528.40 (2.29)	80.99
Selective (entrance examination)		
No	488.57 (1.97)	71.67
Yes	559.26 (3.03)	72.16

Smaller but still considerable mean differences existed between schools according

to their size, with larger schools scoring higher than middle and small schools,

respectively. Schools that charge for tuition score higher than tuition-free schools,

vulnerable schools that receive additional subsidies from the government scored lower

than schools that do not qualify for this benefit, and selective schools scored higher than

schools that do not administer entrance examinations.
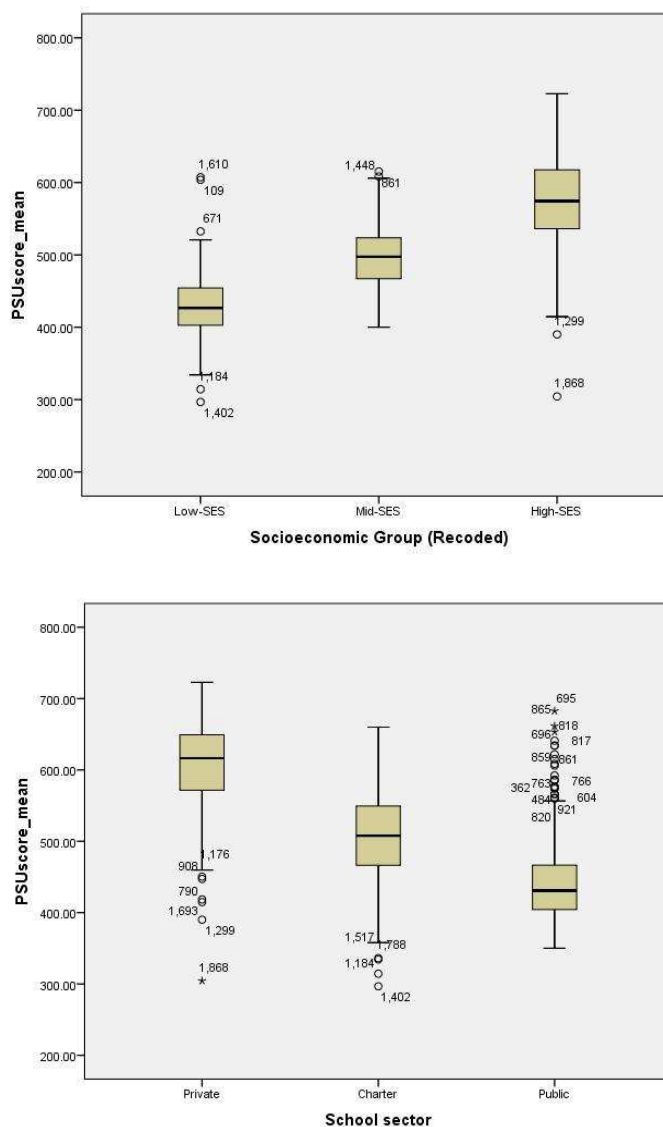
Figure 7. Box and whisker plots of school mean test scores by sector and SES.

Figure 7 depicts box and whisker plots of school mean test scores by school SES

(top panel) and school sector (bottom panel). It is evident that the higher the SES of the

school, the higher students perform, on average, on college admissions tests. In relation

to school sectors, private schools considerably outperformed public and subsidized

private schools. It is also noticeable that there are several outliers within public schools.

After a closer look at these public schools, I discovered that these schools were, on

average, of higher SES than the typical public school. That is why these schools are not

outliers when looking at schools by SES (top panel), because they blend in with the high SES schools.

Overall, the descriptive analysis of students and school variables revealed that performance on admissions tests differed considerably across student groups according to gender, age, income and high school GPA. These findings are consistent with previous studies (Contreras et al., 2007; CTA-CRUCH, 2004; 2005; OECD & The World Bank, 2009; Valdivieso et al., 2006), which indicated that student performance is related to student characteristics such as gender, income and prior achievement.

Also, these descriptive findings showed that there are considerable differences in the average school performance on admissions tests depending upon school structural characteristics (sector, size and subsidies), policies and practices (selectivity and college-going culture), and composition of the student body (average student socioeconomic status and average proportion of females). The descriptive findings also suggested that the student- and school-level variables included in this study may be associated with student performance on college admissions tests.

However, it is important to remember that a descriptive analysis is not able to explain variability in the outcome variable. Therefore, in order to better understand how the student and school characteristics simultaneously explained the variability in the outcome variable, I conducted a multilevel random intercepts and slopes analysis that took into account the nested nature of the data (students nested within schools).

Model Specification

This section describes the stages and specific steps within each stage that I followed to build the model that provided answers to the research questions posed in this study. The model specification took into account three subsequent stages: 1) fitting a null

model, 2) building a within-school model, and 3) building a between-school model. I used HLM7 software to specify this model under restricted maximization likelihood (MLR).

The Fully Unconditional Model (FUM). The first stage in building the model was to fit a fully unconditional model, which yielded estimates of the population mean and the amount of variance in the outcome variable within and between schools. The purpose of specifying such a model was to verify whether there was enough variance to be modeled at the school level. Preliminary analyses indicated that 52.5% of the variability lay between schools. Consequently, the sufficiently high value of this statistic justified proceeding ahead with a multilevel approach to model the variability of the outcome variable.

The Within-School Model. The second modeling stage was devoted to fit a level-1 model or within-school model (with both random and fixed student-level slopes). This model served two purposes: 1) to identify the extent to which students' individual characteristics influence their performance on admissions tests, thus providing an answer to research question 2, and 2) to determine which student-level effects vary across schools at a statistically significant level, thus yielding an answer to research question 3.

The first step in building the within-school model was to incorporate each student-level variable (gender, age, income, sibling in higher education, and high school GPA) one at a time, which Raudenbush and Bryk (2002) referred to as to a "step-up" approach. At first, variables were introduced all group-mean centered, with randomly varying slopes. Then, I re-entered the variables that did not significantly vary across schools as grand-mean centered with fixed errors. I conducted several hypothesis tests to

assess whether fixed effects were significantly different from zero, and I eliminated variables that did not yield significant effects.

I next ran a model that included age, gender, having siblings in higher education, and income as student-level predictors of admissions test scores. This model specified that all slopes varied across schools. However, because only 1,237 out of the 1,887 schools in the sample had enough variability to be modeled when allowing all the slopes to vary, I re-entered the income and siblings in higher education slopes as grand-mean centered with constrained variance. Then, I introduced high school GPA to the model group-mean centered allowing the variance component to vary across schools. The inclusion of this variable in the model resulted in changes in the magnitude and statistical significance of the effects of the other variables in the model. The fact that all these changes were due to the inclusion of GPA in the model indicated that this is a confounding variable, meaning that high school GPA is simultaneously related to the outcome variable and to other predictors in the model as well. Therefore, I created interaction terms between high school GPA and gender, age, and income. However, the interaction terms yielded very small effects that were not statistically significant.

Also, in the within school model I decided to eliminate the variable siblings in higher education from the model because its effect was not significantly different from zero, as determined by a single-parameter hypothesis test (χ^2 statistic = 1.77; $df = 1$ p-value = 0.179) after introducing income to the model. Finally, I added the class rank variable to the within-school model. This variable had a significant effect on the outcome variable even after controlling for high school GPA, and its effect was tested using a single-parameter test. The results of the test showed that this variable's effects are significantly different from zero ($\chi^2 = 210.29$, $df = 1$, p-value = <0.001).

The Between-School Model. The objective of the between-school component of the final model was twofold. First, the objective was to identify the school characteristics that explain the variability of students' performance on college admissions tests between schools, which provided the answer to research question 4. I achieved this by modeling the intercept, which means looking for school variables that predict level-1 intercepts. Secondly, the objective was to determine whether some school characteristics influenced the relationship between students' characteristics and their performance on admissions tests. I accomplished this by modeling the slopes, i.e. looking for school predictors of the slopes. In the process of building the between-school model, as recommended by Raudenbush and Bryk (2002), school variables were incorporated first on the intercept, before proceeding to fit models for the random slopes.

Modeling the Intercept. When fitting a model for the intercept, I introduced the school predictors in the model in subsets corresponding to the three main types of variables identified in the conceptual model of this study in the following order: structure, composition, and practices and policies.

Then, I conducted multivariate hypothesis tests to determine whether a variable should be kept or dropped from the intercept. The results of these tests indicated that all the predictors I finally decided to keep on the intercept were simultaneously significantly different from 0 (χ^2 statistic = 6,790.05, df = 13, p-value = <0.001); i.e., that school sector, school socioeconomic composition, class size, school size, average school GPA, proportion of female students, school selectivity, proportion of students who take admissions tests, and whether schools charge tuition have a simultaneous significant effect on the average school performance on college admissions tests.

Modeling the Slopes. The second step in building the between-school section of the model was to incorporate school-level predictors in the slopes, starting with the introduction of the same set of school predictors that ended up having a significant effect on the intercept in the two varying slopes (female and GPA). I did so in order to avoid the misspecification that could result if the errors of level-2 equations were correlated, which was possible due to collinearity issues (Raudenbush & Bryk, 2002). Then, I conducted multiparameter hypothesis tests to assess whether the fixed effects that were not statistically significant could be eliminated from the initial fitted between-school model that had the same predictors in the intercept and all slopes. For example, for the female slope I found that the coefficients associated with 11 school variables did not contribute significantly to the model ($\chi^2 = 4.03$, *df* $= 10$, *p*-value $= >.500$), so they were eliminated from this slope.

Additionally, I used a second approach to multiparameter hypothesis tests to verify that the variables eliminated from the slopes were in fact not contributing to the model. This approach consisted of using the deviance statistic of the model obtained under full maximum likelihood estimation (MLF) to compare the more complex initial model with the one that excluded the fixed effects hypothesized to be null (Raudenbush & Bryk, 2002, p. 60). The results of this test are displayed in Table 12, and they indicated that the simpler model (the one with fewer fixed effects in the slopes) was a better fit, a result that is consistent with the multiparameter hypothesis tests.

Table 12. *Unrestricted versus restricted model, in relation to fixed effects on the slopes*

Model	Number of Parameters	Deviance	Deviance test
Unrestricted (model 1)	50	1,144,160.63	$\chi^2 = 9.67$ $df= 17$
Restricted (model 2)	36	1,144,167.9	p-value $= >.500$

Once I fitted the fixed effects on the slopes, the resulting model was finally tested against a parallel restricted model, which had the same fixed effects but constrained variance for some of the slopes ($u_{1j} = u_{2j} = 0$). I used the deviance statistic to compare the fit of the unrestricted model to that of the restricted model. Table 13 shows the number of parameters and the deviance statistic for each model. The reduction in deviance is 137.12, which is significant when compared against a χ^2 distribution with 7 degrees of freedom (*p-value* <0.001). According to this criterion, the more complex model is significantly enhanced by specifying the residuals of the slopes as random. This conclusion is also supported by the Akaike's information criterion (AIC) and the Bayesian information criterion (BIC), which are smaller in the case of the unrestricted model.

Table 13. *Fit assessment of unrestricted versus restricted random effects model*

Model	Number of Parameters	Deviance	Deviance test	AIC	BIC
Unrestricted (model 1)	7	1,144,113.6	$\chi^2 = 590.2$ $df = 5$	1,144,127.6	1,144,151.2
Restricted (model 2)	2	1,144,692.8	p-value $= <0.001$	1,114,696.8	1,144,707.9

Finally, I tested the final model for homogeneity of variance at level 1 and found that there was heterogeneity of variance at the student level (χ^2 statistic $= 5700.8$, $df = 1701$, p-value < 0.0001). Therefore, I ran a model allowing the level-1 variances to be unequal, and modeled the variance using student and school predictors. Although the model that allowed level-1 variances to be unequal had a better fit than the model that

assumed homogeneity of variance (χ^2 statistic = 2753.8, *df* = 9, *p*-value < 0.0001), because the coefficients of fixed and random effects did not change at all, I decided to keep the results of the former model with homogenous level-1 variances.

The Final Analytical Model

After the specification of the model, I ran a final intercepts- and slopes-as-outcomes model, which estimated fixed and random effects of student and school variables on student performance on college admissions tests.

The equations corresponding to the final model are presented below. These equations indicate that at the student level, performance on college admissions tests depends on the student's age, gender, income, GPA, and class ranking. At the school level, the model indicates that the average performance of a school on college admissions tests is determined by school sector, school socioeconomic status, school size, average class size, the proportion of students who took admissions tests, the average GPA at the school, the proportion of female students in the school, whether the school administers entrance examinations for selection purposes, whether the school charges for tuition, and whether the school receives a preferential subsidy from the state. This model also reveals that the relationship between student performance on college admissions tests and gender varies between schools, and that this relationship is moderated by the average class size and the proportion of female students at a given school. Also, the relationship between student performance and GPA varies across schools, and this variability is due to differences in school sector, school size, the proportion of students who take admissions test within the school, and the average GPA at the school. The results yielded by this analytical model are presented in Table 14.

Level 1 Model

$$PSU\ score_{ij} = \beta_{0j} + \beta_{1j}\left(Older_{ij} - \overline{Older}_{..}\right) + \beta_{2j}\left(Female_{ij} - \overline{Female}_{.j}\right)$$
$$+ \beta_{3j}\left(Mid\_Inc_{ij} - \overline{Mid\_Inc}_{..}\right) + \beta_{4j}\left(High\_Inc_{ij} - \overline{High\_Inc}_{..}\right)$$
$$+ \beta_{5j}\left(ZHSGPA_{ij} - \overline{ZHSGPA}_{.j}\right) + \beta_{6j}\left(Top\ ten_{ij} - \overline{Top\ ten}_{..}\right) + r_{ij}$$

Level 2 Model

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(Pref\_Sub_j) + \gamma_{02}(Adm\_Test_j) + \gamma_{03}(Private_j) + \gamma_{04}(Sub\_Private_j)$$
$$+ \gamma_{05}(Medium_j) + \gamma_{06}(Large_j) + \gamma_{07}(Tuition\_free_j) + \gamma_{08}(Mis\_SES_j)$$
$$+ \gamma_{09}(High\_SES_j) + \gamma_{010}(Zclass\_size_j) + \gamma_{011}(ZPSU\_Stud_j)$$
$$+ \gamma_{012}(ZFemale\_mean_j) + \gamma_{013}(ZGPA\_mean_j) + u_{0j}$$

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

$$\beta_{2j} = \gamma_{20} + \gamma_{21}\left(Zclass_{size\ j}\right) + \gamma_{22}(ZFemale\_mean_j) + u_{2j}$$

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

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

$$\beta_{5j} = \gamma_{50}$$

$$\beta_{6j} = \gamma_{60} + \gamma_{61}(Private_j) + \gamma_{62}(Sub\_Private_j) + \gamma_{63}(Medium_j) + \gamma_{64}(Large_j)$$
$$+ \gamma_{65}(ZGPA\_mean_j) + u_{6j})$$

where:

Older:	Older students of the cohort (Born in 1990 =1; Born in 1991 or after = 0)
Female:	Gender (Female =1, Male =0)
Mi_Inco:	Middle-income students (Middle-income =1, Low-income = High-income=0)
Hi_Inco:	High-income students (High-income =1, Low-income = Middle-income=0)
Topten:	Students ranked top ten percent in their school
ZHSGPA:	Student high school grade point average (standardized)
Pref_Sub:	Schools receive state preferential subsidy (yes = 1, no= 0)
Adm_Test:	Schools administer entrance examination (yes = 1, no= 0)
Private:	Private schools (Private = 1, Public = Subsidized private = 0)
Sub_Private:	Subsidized private schools (Subsidized private = 1, Public = Private = 0)
Medium:	Medium size schools (Medium= 1, Small = Large = 0)
Large:	Large size schools (Large= 1, Small = Medium = 0)
Tuition:	Whether schools charge for tuition (yes = 1, no= 0)
Mid_SES:	Middle school socioeconomic status (Middle =1, High = Low = 0)
High_SES:	High school socioeconomic status (High =1, Middle = Low = 0)
Zclass_size:	Average class size (standardized)
ZPSU_Stu:	Proportion of students who took admissions tests (standardized)
ZFemale_mean:	Proportion of female students (standardized)
ZGPA_mean:	Average school GPA (standardized)

Table 14. *An intercept- and slopes-as- outcome model of performance in college admissions tests*

Fixed Effects	Score points (se)		Effect in SD (se)		p-value
Intercept, β_{0j}					
Average school mean*, γ_{00}	465.1	(4.9)			<0.001
Private, γ_{01}	55.4	(4.2)	1.72	(0.13)	<0.001
Subsidized private, γ_{02}	9.6	(3.3)	0.30	(0.10)	0.005
Middle-SES school, γ_{03}	21.8	(3.1)	0.68	(0.10)	<0.001
High-SES school, γ_{4}	47.0	(3.8)	1.46	(0.12)	<0.001
Medium size, γ_{05}	10.4	(2.2)	0.33	(0.07)	<0.001
Large size, γ_{06}	26.7	(3.1)	0.83	(0.10)	<0.001
Average class size (standardized), γ_{07}	9.4	(1.4)	0.29	(0.04)	<0.001
Prop. of students taking adm. tests, γ_{08}	9.4	(1.2)	0.29	(0.04)	<0.001
Average school GPA, γ_{09}	52.5	(2.1)	1.63	(0.07)	<0.001
Proportion of females, $\gamma_{0,10}$	-3.9	(4.8)	-0.11	(0.15)	<0.001
Entrance examination, $\gamma_{0,11}$	9.6	(1.9)	0.29	(0.06)	<0.001
Tuition-free, $\gamma_{0,12}$	-11.8	(3.1)	-0.37	(0.10)	<0.001
Preferential State Subsidy, $\gamma_{0,13}$	-8.4	(1.9)	-0.26	(0.05)	<0.001
Older student slope, β_{1j}					
Intercept, γ_{10}	-9.9	(0.7)	-0.30	(0.02)	<0.001
Female slope, β_{2j}					
Intercept, γ_{10}	-30.3	(2.3)	-0.94	(0.07)	<0.001
Class size (standardized), γ_{11}	1.2	(0.5)	0.04	(0.02)	0.007
Proportion of females, γ_{12}	-2.1	(0.8)	-0.07	(0.13)	0.009
Middle-income slope, β_{3j}					
Intercept, γ_{30}	5.4	(0.5)	0.17	(0.02)	<0.001
High-income slope, β_{4j}					
Intercept, γ_{40}	10.6	(0.5)	0.33	(0.02)	<0.001
Top ten class ranking slope, β_{5j}					
Intercept, γ_{50}	10.9	(0.7)	0.34	0.02	<0.001
High school GPA slope, β_{6j}					
Intercept, γ_{60}	50.8	(1.2)	1.58	(0.04)	<0.001
Private, γ_{61}	-2.4	(1.0)	-0.07	(0.03)	0.019
Subsidized private, γ_{62}	-2.7	(0.7)	-0.08	(0.02)	0.006
Medium size γ_{63}	2.2	(0.8)	0.07	(0.02)	<0.001
Large size, γ_{64}	3.4	(0.9)	0.10	(0.03)	<0.001
Prop. of students taking adm. tests, γ_{65}	4.1	(0.4)	0.13	(0.01)	<0.001
Average school GPA, γ_{66}	8.3	(0.4)	0.26	(0.01)	<0.001
Random Effects	Variance component		Reliability		
School means (intercepts), u_0	1035.9		0.923		<0.001
Female, u_2	55.9		0.183		<0.001
High School GPA, u_6	51.8		0.369		<0.001
Level-1, r_{ij}	2566.8				

* This is the mean for the reference group, represented by an hypothetical type of student who is male, born in 1991 or after, low-income, of average GPA, studying at a hypothetical school, which is public, low-SES, and small, that charges tuition, has an average proportion of female students, does not select student, has an average class size, an average aggregated GPA, and an average amount of students taking admissions tests.

Results by Research Questions

Research Question 1. The first research question of this study asked whether students' performance on college admissions tests varies across Chilean high schools. The answer to this question is provided by the fully unconditional model (One-Way ANOVA with random effects), which yields estimates of the population mean and the amount of variance in the outcome variable that lies within and between schools. Table 15 provides estimates of the school grand mean (γ_{00} = 514.22), the variance of the school means around the grand mean (u_0 = 5671.69), and the within level variance (r_{ij} = 5168.97).

Table 15. *Results from the Fully Unconditional Model*

Fixed Effect	Coefficient	Standard error	
Average school mean, γ_{00}	514.22	1.76	
Random Effect	*Variance component*	*p-value*	*Reliability*
School means (intercepts), u_0	5671.69	<0.001	0.969
Student-level, r_{ij}	5168.97		

Because the estimate of the between-variance (u_0) is significantly different than zero (χ^2 = 115,449.2, *df* = 1,886, *p-value*<0.001), it can be concluded that there is a statistically significant variation of the admissions tests score means across schools, which is the answer to the first research question. The magnitude of this variability can be obtained with 95% confidence, i.e. the range of plausible values within which the school means fall:

$$\left[\gamma_{00} \pm 1.96 \sqrt{u_{0j}}\right] = \left[514.22 \pm 1.96\sqrt{5671.69}\right] = [366.6, 661.6] \tag{1}$$

Additionally, using the estimates of the variance components obtained with the fully unconditional model, I obtained the intraclass correlation (ICC) coefficient.

$$ICC = \frac{\widehat{\tau_{00}}}{\widehat{\sigma^2} + \widehat{\tau_{00}}} \times 100 = \frac{5671.7}{5671.7 + 5168.9} \times 100 = 52.3\% \tag{2}$$

The ICC indicates that more than 52% of the variability in admissions tests scores

lies between schools. These proportions suggest substantial academic stratification within

the Chilean school system. Additionally, the ICC obtained provides empirical support for

the need to use multilevel methods beyond the theoretical rationale of the nested nature of

the data and the violation of independence of observations within schools.

Research Question 2. The second research question inquired about individual

student characteristics that predict performance on college admissions tests among

Chilean high school graduates. The final model indicated that age, gender, income, high

school GPA, and class ranking had a statistically significant impact on these students'

performance on college admissions tests. Having siblings in higher education was found

not to be significantly related to the outcome variable after controlling for students'

income.

The extent to which these individual characteristics affect student performance on

college admissions tests is demonstrated by the fixed effects associated with the slopes

($\gamma_{10}, \gamma_{20}, ..., \gamma_{60}$ in Table 14). High school senior students that are older than other students

their cohort (born in 1990 or before) scored on average almost 10 score points (0.30 SD)

lower than their younger classmates. Female students were also at a disadvantage, scoring

30.3 points lower than male students, which is an effect size of almost 1 SD. This effect

varied significantly across schools from -44.7 to -15.4 points. High-income and middle-

income students scored 5.4 and 10.6 points higher than their low-income counterparts,

although the effect size was small (0.17 and 0.33 SD, respectively) (Cohen, 1998).

Students' high school GPA had the largest effect on their performance on admission test. One SD increase in student GPA resulted, on average, in an increase of 50.8 points on the tests, an effect of 1.58 SD. This effect significantly varied across schools, fluctuating from 35.8 to 64.4 points. On average, students ranked in the top ten percent of their class scored over a third of a SD (11 points) higher than lower achieving students, even after controlling for GPA.

Research Question 3. This question asked whether the relationship between students' individual characteristics and their performance on college admissions tests varies across schools. This means looking at the slopes that vary significantly across schools. In the final intercepts- and slopes-as outcome models, only the female and GPA slopes were allowed to vary across schools[2]. The variation of these slopes was statistically significant (p-value <0.001). In the case of females, the effect of this variable on performance on college admissions tests varied significantly from -44.7 to -15.4 points. This means that, on average, female students scored lower than their male counterparts in every school, but the gender gap in test scores was as low as 15.4 points (0.3 SD) at some schools and as high as 44.7 points at other schools (1.2 SD).

The effect of students' GPA on their performance on college admissions tests also varied between schools. On average, one SD increase in GPA resulted in at least 35.8 (1.1 SD) points for students at some schools and up to 64.4 (1.9 SD) at others. Figure 8 portrays high school GPA slopes for ten different schools in the sample. It can be seen that the slopes are all positive, meaning the higher the students' GPAs, the higher the scores they earned on the college admissions tests. However, some of the slopes are

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[2] In the first stages of the specification of the model, I found that age, gender, income, and high school GPA all varied significantly across schools. However, because a big proportion of schools did not have enough variability to model when allowing all slopes to vary, and based on the relatively low reliability of some of the slopes, I decided to fix the slopes related to income and age.

steeper, which suggests a stronger impact of students' GPA on their performance on admissions tests than schools in which the slope is flatter.
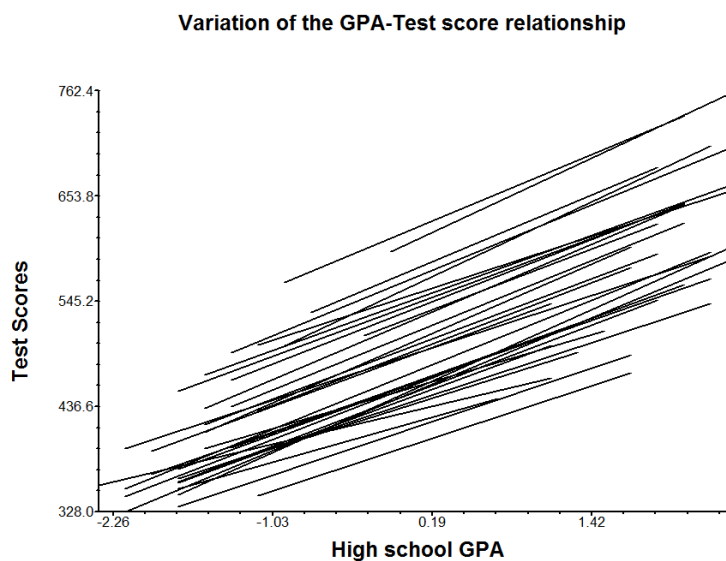
Figure 8. High school GPA-test score slopes for a random subset of schools in the sample.

Research Question 4. This question asked about the school characteristics that have an impact on student performance on college admissions tests. The answer to this question can be found in the upper section of Table 14. The differences in the average school means are explained by the following school characteristics: sector, average SES of the student body, school size, average class size, the proportion of students who take admissions tests within the school, the average school GPA, the proportion of female students, selectivity (whether they administer entrance examinations), and whether or not the school charges for tuition.

Structural School Characteristics. School sector had the largest effect on school means of students' performance on college admissions test scores. Students from private schools scored, on average, 55.4 points higher than students in public schools. This corresponds to an effect size of 1.7 SD, which is an enormous effect (Cohen, 1998). The

gap between subsidized private and public schools is significant, but smaller. On average, students in subsidized private schools scored almost 10 points (0.30 SD) higher than students in public schools, which according to Cohen (1998) is a moderate effect size.

School and class size also had an impact on student performance on college admissions tests. Students attending large schools (more than 1,000 students) scored, on average, 26.7 points (0.83 SD) higher than those attending small schools (less than 400 students). The test score gap between students attending small and medium-sized schools (between 400 and 1,000 students) is moderate (0.33 SD) and statistically significant. This result contradicts Arzola and Troncoso's study (2011) of the effect of school size on academic performance as measured by standardized reading and math tests in elementary schools. The contradicting results might be due to the use of different outcome variables, or different categorization of school size. While I recoded this variable into three categories, Arzola and Troncoso (2011) categorized this variable into five brackets. It is also important to remember that school size is a highly skewed variable.

Regarding average class size, for each SD increase in class size, students score almost 10 points (0.29 SD) higher. Whether or not schools charge for tuition also impacted the average performance of the school on admissions tests. Students attending tuition-free schools scored, on average, 11.8 points (0.37 SD) lower than their peers who attended schools that charge tuition. Students attending schools that receive additional subsidies from the government scored 8.4 points lower (0.26 SD) than those who attended more privileged schools that did not need this type of assistance.

Compositional School Characteristics. A school's average GPA at a particular school has a large effect on its students' performance on admissions tests. One SD increase in a school's average GPA resulted in an average 52.5 point increase in

admissions test scores (0.163 SD). This effect holds true after controlling for individual

GPA, which means that GPA has a contextual effect above and beyond the effect of

individual GPA on student performance on college admissions tests. The contextual

effect is the "expected difference in the outcomes between two students who have the

same individual GPA, but who attend schools differing by one SD in average GPA"

(Raudenbush & Bryk, 2002, p. 141).

Also, schools serving high SES students scored 49.3 points (1.5 SD) higher than

schools serving less privileged students. It is important to acknowledge that the model

already controlled at level-1 for individual income, which is a good proxy of

socioeconomic status. Therefore, the fact that school SES had a large effect on the

average school performance reveals that there is a compositional or contextual effect of

socioeconomic status above and beyond the individual effect. This means that student

performance is not only determined by individual SES, but also by the average SES of

students' peers.

The proportion of female students enrolled at schools also influenced individual

student performance, even after controlling for gender at the individual level. A one SD

increase in the proportion of female students at a school produced an average decrease in

that school's mean score of 3.9 points (0.15 SD). Although significant, this is a relatively

small effect (Cohen, 1998).

School Practices and Policies. Students attending schools that administer

entrance examinations for admissions purposes scored, on average, 9.6 points (0.29 SD)

higher than students who attended schools with open admission. This finding is

consistent with Contreras and colleagues (2010), who found that schools that select

students outperform schools that do not implemented this practice. Also, the college-

going culture of a school, measured by the proportion of students who take admissions tests, had a moderate (Cohen, 1998) but significant effect on student scores on admissions tests. A SD increase in the proportion of students who take the tests resulted in an increase of 9.4 points (0.29 SD) on the test.

Research Question 5. This question inquired about the extent to which school characteristics influence the relationship between students' characteristics and their performance on admissions tests. This required an examination of the female and GPA slopes (β_{2j} and β_{6j}) to determine if school-level and aggregated student-level variables had an effect on these slopes. This phenomenon is also referred to as a cross-level interaction (Luke, 2004).

The Female Slope. Only two school-level variables were found to have a significant effect on the female slope. The female slope was slightly moderated by class size and slightly exacerbated by the proportion of female students within the school. On average, the slope for a school with average class size was -30.3 points; for schools with larger class size (+1SD) the female-performance slope was -29.1, while for schools with smaller class size (-1SD) the gap for female students was higher (-31.4 points). This means that, on average, schools with a larger class size to some extent obtained more equitable results for students of different gender. On the other hand, a greater proportion of female students in a school negatively affected the individual performance of female students. A one unit increase in the proportion of female students at the school widened the gap for female students by 2.1 points (0.13 SD).

The GPA Slope. The variability across schools associated with high school GPA was explained by school sector, school size, the proportion of students taking admissions

tests, and the average GPA of the school. The magnitude of the effects can be seen at the bottom of Table 14.

The performance-GPA slope was moderated at private and subsidized private schools by 2.4 and 2.7, respectively. This means that the slope is flatter at subsidized private and private schools; i.e., that the relationship between GPA and performance on college admissions tests is slightly weaker in subsidized private and private schools as compared to public schools. On the contrary, as school size increased, the performance-GPA slope became steeper by 2.2 points in medium-sized (between 400 and 1,000 students) schools and by 3.3 score points in large schools (more than 1,000 students). In other words, GPA is a weaker predictor of college admissions test performance in small schools.

Also, the composition of the student body had an impact on the performance-GPA slope. As the proportion of students who took admissions tests and the average GPA at the school increased, the performance-GPA slope became steeper by 4.1and 4.2 points, respectively. This means that in schools with a higher proportion of students who took admissions tests, and in schools with higher average GPA, individual GPA is a stronger predictor of student performance on college admissions tests.

Explained Proportion of Variance and Model Fit

As a final step, I obtained the proportion reduction in variance for the residuals at level-1, for the intercept, and for the slopes. The results of this calculation correspond to the percent reduction in each variance component obtained in each of the subsequent stages of the model specification: the null model, the within-school model, and the between-school model.

Table 16. *Percentage of variance explained and deviance statistic for the null, within-school, and final random intercepts and slopes model.*

	Variance Component			% of Variance Explained
	Null Model	Within Model	Final model	
Student-level, r_{ij} *sigma*	5,169.0	2,565.8	2,566.8	50,3%
Intercept, u_{0j} *tau*	5,671.7	5,266.6	1,035.9	81.7%
Female slope, u_2	-	55.8	55.8	0.0 %
High school GPA slope, u_6	-	88.6	50.6	42.8%
	Model Fit			
	Null Model	Within Model	Final model	
Deviance statistic	1,219,062.2	1,146,547.3	1,144,162.7	
parameters	3	14	35	

As it is illustrated in Table 16, the final model successfully explained 50% of the variance at the student level (within schools). Thus, there is 50% of variance within schools left to be explained by other factors. Also, the final model explained 81.7% of the variance in the intercept (between schools). This means that the variables included in the model successfully explained the variability of school mean test scores. The model also was able to find school characteristics that account for the variability in the high school GPA slope, although there is more than 57% of the variance that is still unexplained. Finally, the final model was not able to explain the variability in the female slope (0.0%). This means that the school characteristics that could moderate the gap in test scores of female and male students were not the ones included in the model.

Regarding model fit, I used the deviance statistic obtained through full maximum likelihood estimation (MLF) to compare the within-school model with the null, and the final model with the thin school model to test in each case whether the more complex model had a better fit (McCoach, 2010). When using the deviance statistic to compare

models, if the additional parameters added to the model reduce deviance by a substantial amount, then the more complex model can be retained.

I first compared the within-school model against the null model (χ^2 = 72,514.9, *df* = 11, *p*-value = <0.001), the deviance reduction was statistically significant, so the more complex model (i.e., the within-school model) has a better fit than the null model. Then, I compared the final random intercepts and slopes model against the within-school model (χ^2 = 2,384.6, *df* = 21, *p*-value = <0.001), and the final model has a statistically significant better fit than the within-school model.

Chapter 5: Discussion and Conclusions

Introduction

Access to higher education in Chile has steadily increased in the last two decades. In 1990 there were almost 250,000 students enrolled in all postsecondary institutions, while in 2005, this number increased to more than 660,000 (Uribe & Salamanca, 2007). Although low-income students almost tripled their participation in higher education in the period of 1990 to 2005 (from 4.4% to 14.7%), they are still far from reach the levels of participation of high-income students, who increased their enrolment in higher education institutions from 41% to 74% in the same period. In turn, this inequality of access to higher education appears to be related to the systematic performance gap in college admissions tests associated with students' family income, parental education, and the type of school attended (Contreras, Corbalán, & Redondo, 2007; CTA-CRUCH, 2004; 2005; Koljatic & Silva, 2006; 2010; OECD & The World Bank, 2009).

Student performance on admissions tests is critical to gaining admission to publicly funded colleges and universities as these rely almost exclusively on admissions test scores to select students (OECD & The World Bank, 2009). Additionally, performing well in college admissions tests is decisive to being admitted to certain majors, and to apply or qualify for state financial aid (MINEDUC, 2011; OECD & The World Bank, 2009). As a result of these admission and financial aid policies, college admissions tests have become a considerable barrier to gaining admissions to college, to choosing a major and to obtaining financial aid for underrepresented groups of students who have systematically scored lower on admissions tests than their more privileged counterparts (OECD & The World Bank, 2009).

The purpose of this study was to examine the student and school characteristics that are more likely to impact performance on admissions tests in Chile. The research questions guiding this study asked about the extent to which performance on college admissions tests varies across schools, the student characteristics that predict performance within schools, and the school characteristics that explain the score gap between schools.

Based on the American and Chilean literature on this topic (e.g. Adelman, 2006; Contreras et al. 2007, 2009; Lee, Bryk, and Smith, 1993; Zwick, 2002), I hypothesized that both individual agency and school characteristics would have an effect on student performance. Consequently, I proposed a conceptual model that advances a structure whereby students are nested within schools. This model assumes that: 1) at the school level, students are affected by the particular contexts of their respective schools, not only by the structural school characteristics but also by the aggregated social and academic characteristics of their peers, as well as school practices and policies; and 2) at the individual level, socioeconomic status, academic achievement, and demographic characteristics impact student performance on admissions tests. Finally, the model assumes that there are cross-level interactions; i.e., that some school characteristics and aggregates of student characteristics may influence the relationship between students' predictors and outcomes.

This chapter discusses the main findings that provide answers to the five research questions that guided this study. It also refers to the implications that these results may have for policy and research. First, I discuss the main findings corresponding to each research question and how they align with the existing literature and the study's hypothesis. Then, in the conclusions section I highlight and summarize the main results

of the study. Finally, the last sections of this chapter refer to implications for research and policymaking, acknowledgment of the limitations of this study, and recommendations for future research.

Discussion by Research Question

The study provided evidence that confirmed all hypotheses initially posed. First, the fully unconditional model's results confirmed that performance on college admissions tests among Chilean high school graduates varies between schools. Also, the study provided evidence that performance among Chilean high school graduates is determined both by individual and school characteristics, and that some school characteristics moderate the effects of individual student predictors on performance. Next, I discuss in more detail the findings associated with each research question.

Research Question 1. This question asked whether student performance in college admissions tests varied between schools. More than fifty percent of the variability of students' scores on admissions tests is determined by the school they attend. This high intraclass correlation (ICC) also suggests high levels of school segregation given that student performance varies less within schools than between schools.

This finding is consistent with the ICC obtained in prior achievement assessments in Chile, such as the Programme for International Student Assessment (PISA), which found an average ICC between math and reading tests of 51% in 2000 and 52.5% in 2006 for Chilean schools (OECD, 2009). This ICC for Chilean schools in performance is relatively higher than that of many other countries, even when compared to other Latin American developing countries. For example, the 2006 PISA study found that the ICC for the United States was approximately 25% and for Norway it was 11%,

while for other Latin American countries, such as Colombia and Uruguay, the ICC was approximately 35% and 40% (OECD, 2009), respectively.

Research Question 2. This question inquired about the individual characteristics that predict performance on college admissions tests. Previous research had reported differences in mean scores favoring males and high-income students (Contreras, Corbalán, & Redondo, 2007; CTA-CRUCH, 2004; 2005; Koljatic & Silva, 2006; 2010; OECD & The World Bank, 2009). Similarly, the results of this study indicated that female and low-income students score lower on admissions tests than their male and more privileged counterparts.

Additionally, I found that prior academic performance in high school, as measured by students' high school GPA, plays a substantial role in their performance on admissions tests. Actually, students' GPA had the largest effect on the outcome variable among individual predictors. These findings are consistent with Contreras and associates' (2007), who found that GPA in both elementary and secondary schools explained most of the variability in students' scores on admissions tests.

What is new about this study is that I also tested whether the relative academic performance, as measured by class ranking, had an influence on students' performance on college admissions tests. I found that students with higher GPAs within their schools (top ten percent) score higher on college admissions tests than their classmates, even after controlling for GPA. To my knowledge, this is the first quantitative study that provides evidence regarding the positive effect of the relative academic ability of students on performance on college admissions tests in Chile.

This study is also the first one to reveal that older students in the cohort score lower than their younger counterparts. The reasons why there are older students in a

particular cohort may be due to the fact that some students that were held back a grade during elementary or secondary school, or because students that entered elementary school at an age older than required (six years old). Further analyses need to be done in order to explain why there is a proportion of student older in a cohort, and why these students score lower than their younger counterparts.

Research Question 3. The third research question asked whether the relationship between individual predictors and performance on college admissions tests was different among schools. Results indicated that the relationship between performance on admissions tests and two individual predictors, namely high school GPA and gender, varied significantly across schools. In relation to GPA, this means that in some schools the impact of high school GPA on test scores is stronger than in others, but the direction of the average effect of GPA was positive across all schools. In other words, in all schools students with higher GPAs will score higher on admissions tests than students with lower GPAs, although the intensity of this effect is not the same across schools. As for gender, on average, females scored lower than males in every single Chilean school, although the gap differed significantly in magnitude between schools. To my knowledge, this finding has not been reported in other Chilean studies.

Research Question 4. This research question inquired about the school characteristics that explain the differences in average test scores between schools. I found that this variation is mostly explained by average socioeconomic status (SES) of the school, school sector, and school size.

The study's results evidenced that the average SES of the school has a compositional or contextual effect on admissions test scores. A contextual effects exist when the aggregate (school average) of a student-level characteristic has an impact on the

outcome variable even after controlling for the effect of that same student characteristic at the student level (Raudenbush & Bryk, 2001). In this case, I found that the average SES of the student body has an effect on individual performance in admissions tests that goes above and beyond the effect of individual SES, as measured by individual family income. This contextual effect is almost one and a half SD, which is quite large (Cohen, 1998). This finding is consistent with a large body of American literature that has provided strong evidence about the compositional effects of the SES of the student body on individual academic performance (e.g. Lee et al., 1993; Myers et al., 2004; Sirin, 2005; Stewart, 2008).

In relation to school sector, the results of this study indicated that private schools significantly outperform public schools. The gap between public and private schools is substantial, with public schools scoring 1.7 SD lower than private schools. In other words, students in a typical private school score, on average, 41 percentile points higher than students in an average public school. Although subsidized private schools also outperform public schools, the scoring gap between them is only one third of a SD. This means that students of a typical subsidized private school, on average, outperform students of a typical public school by 8 percentile points. This private school advantage remains even after controlling for the compositional effect of socioeconomic status of the school and for school selectivity (whether the school administers entrance examination for selection purposes), which means that there is something other than SES and selectivity that explains the superiority of private schools' performance on admissions tests. The gap among private, subsidized private and public schools found in this study is consistent with prior research conducted in Chile, which found that school sector has a strong impact on students' performance on admissions tests. These studies have reported

that students attending public high schools have consistently scored lower than students attending private and subsidized private schools (CTA-CRUCH, 2004; 2005; OECD & The World Bank, 2009).

In relation to school size, the findings indicated that as the school size increases, the average performance of students attending the school also increases. This contradicts the results of prior research, which indicated that smaller school sizes result in higher scores on standardized tests among elementary students (Arzola & Troncoso, 2011). These contradictory findings could be due to methodological differences, or because the effects of school size on performance in admissions test may be spurious. In other words, it might be the case that the effect of school size is either moderated or mediated by other school characteristics, such as school resources, infrastructure, and principal's leadership that this study didn't control for.

The proportion of students taking admissions tests also influences the variability in school means. The higher the proportion of students who take the admissions test within a school, the higher the school mean of admissions test scores. The proportion of students who take the admissions test within a school may be reflecting what some researchers define as college-going culture (Corwin & Tierney, 2007; McClafferty McDonough, & Nunez, 2002), which increases the chances of students following the necessary steps to get to college.

Research Question 5. This research question asked about the school characteristics that moderate the relationship of individual predictors (GPA and gender) on student performance. I found that the relationship between gender and performance in college is influenced by class size and the proportion of female students within a school. On one hand, the gender gap increases as class size decreases. Also, female students tend

to score even lower in schools in which the proportion of females in the schools is higher. However, the explanatory power of these two variables is very low, as most of the variability in the gender slope was left unexplained (89%). Studies in the United States have reported that the performance gap between genders may be due to different course-taking patterns in high school, societal stereotypes, and test bias (Forest & Kinser, 2002; McKay et al., 2003). Other researchers have also found that teacher gender, teacher expectations, and student engagement play an important role in female students' achievement (Dee, 2007). These factors may also be influencing performance on college admissions tests among Chilean female students and further analyses should corroborate or disprove this.

As for individual GPA and its relationship to performance on admissions tests, I found that this relationship is moderated by school sector, school size, the proportion of students who take admissions tests, and the average GPA at the schools. In public schools, GPA is a slightly stronger predictor of performance than in private and subsidized private schools. In addition, the predictive ability of GPA on performance increases as school size and proportions of students taking admissions tests increase at a given school.

Finally, the relationship between individual GPA and performance is intensified by the average GPA of the school. In schools where the aggregated GPA of the student body is higher than average, individual GPA better predicts performance on admissions tests. It is worth noting that these school characteristics (sector, size, proportion of students taking admissions tests, and average school GPA) only partially explain the variability in the outcome variable (only 43% of the variance).

Conclusions

In Chile, as far as 2009 is concerned, student performance on college admissions tests is mostly determined by the school they attend. As expected, the intra-class correlation indicated that there is more variability between schools than within schools, which is not surprising given the high socioeconomic segregation of Chilean schools. Actually, most of the difference in average scores between schools is an effect of school sector and the socioeconomic status of students at that particular school.

Although student characteristics are responsible for less than a half of the variability in admissions tests scores, individual characteristics still influence student performance. This study found that students' academic achievement, as measured by their GPA during high school, is the most important predictor of performance on admissions tests, after controlling for gender and individual income. The effect of academic achievement has such an impact on performance that high-achieving students (those in the top ten percent) outperform their classmates, even after controlling for GPA and type of school attended.

This study also provided evidence that students' family income and gender have a significant effect on performance on college admissions tests. In every single school, female and low-income students obtain, on average, lower scores than their male and more privileged counterparts.

Because in Chile colleges and universities rely almost exclusively on admissions test scores to select students, this study's results imply that students' chances of getting admitted into college are mostly determined by the type of school they can afford to attend. Although individuals may increase their chances through superior academic performance in high school, these individual efforts are shaped by the type of school the

student attended. Consequently, admissions tests constitute a great barrier to access to higher education for students that attended public and/or more disadvantaged schools, and these barriers are even harder to overcome for female and low-income students.

Implications

Implications for Policy and Practice. The results of this study have important implications for policymaking, as they show that state policies regarding admissions, financial aid, and public funding of postsecondary institutions do not seem to be aligned with the government's explicit efforts to reduce inequality of access to higher education. Today, Chilean publicly funded colleges and universities rely almost exclusively on test scores to select students. Moreover, the Chilean government requires students to score above a minimum threshold on admissions tests to provide need-based financial aid. The government also allocates additional funds to postsecondary institutions that enroll students who earned high scores on the admissions test (Hudson, 1994; OECD & The World Bank, 2009).

In the light of the results of this study, which has proven that performance on college admissions tests depends more on which school students could afford to attend than on their individual agency, these policies constitute great barriers for access to postsecondary institutions and financial aid, especially for graduates of public schools and low-income and female students. Therefore, changes need to be made in admissions policies, financial aid, and public funding of postsecondary institutions in order to increase access to higher education for traditionally excluded groups in Chilean society.

Based on the study's findings, publicly funded colleges and universities may consider including class ranking as an additional individual factor in the selection of students. This study provided evidence that, on average, students with relatively higher

GPAs (those in the top ten percent of the cohort) score higher on college admissions tests than their classmates, even after controlling for individual high school GPA. Considering class ranking as an additional admission factor would increase the chances of high achieving students of public and/or more disadvantaged schools to gain admission to college. This suggestion is also supported by prior studies in Chile have found that students who outperform their peers in high school have higher chances than their peers to be successful in college (Gallegos, 2006; Gil & Ureta, 2005).

Another implication of this study on admissions policies is the fact that GPA is the best individual predictor of performance in college admissions test. Given this finding, high school GPA could have a higher relative weight than it has now among admissions factors. There are studies in the United States that have found that using admissions tests scores coupled with GPA as predictors of college performance increases predictive validity and reduces under prediction for female students (e.g. Elliott & Strenta, 1988; Zwick & Himelfarb, 2011).

In relation to financial aid policies, this study found that low-income students, on average, score below the minimum thresholds required to apply for need-base financial aid. This negatively affects these applicants' chances of qualifying for state financial aid, further reducing their chances of attending college. This should encourage policymakers to consider rescinding the test score requirements currently used to determine students' eligibility for state need-based financial aid.

This study supported prior studies' conclusions (Contreras et al., 2007, 2009; Matear, 2006; Valdivieso et al., 2007) regarding the high levels of inequity in the Chilean system of admission to college. In spite of this evidence, each year, the Chilean government allocates additional state appropriations to those institutions that enroll the

27,500 students that obtained the highest scores on admissions tests. Undoubtedly, these high-achieving students would have been admitted to any higher education institution even without this institutional economic incentive. Instead, educational authorities should consider providing additional resources to institutions that recruit students who outperform their peers on college admissions tests and come from low-income backgrounds and public schools. For example, in the United States, the State of Texas implemented a top ten percent plan that gave *de facto* access to flagship state universities. This plan successfully increased access to higher education for underrepresented students (Long, Saenz & Tienda, 2010). Another successful experience with this type of policy was the plan implemented by Universidad de Santiago during 1992 and 2003 that rewarded students who had relatively higher high school GPAs (top 15 percent) with additional points on the admissions tests (5% of their total score). Using propensity score matching methods, Gallegos (2007) found that students who benefited from this program performed better, on average, in their first year of college than students with similar characteristics who did not qualify for this reward.

Another important implication of this study relates to the scoring gap between private, subsidized private and public school. Students who attend public schools score much lower than those who attend private schools, and although students at subsidized private schools perform better than those at public schools, they are still behind in relation to private school students. These results suggest that the Chilean government strategy of providing public subsidies to private schools (subsidized private schools) is not the best solution to provide tuition-free and high quality education to middle- and low-income students. In the long run, policymakers should instead consider further investing in and improving the quality of public schools, which mostly serve low-income

students. According to the findings of this study, this is the group of students who needs the most assistance to improve their academic achievement and therefore increase their chances of gaining access to higher education.

Implications for Theory and Research. This study has contributed to the research and theory on access to higher education in Chile in two ways. First, to my knowledge, this study is the first related to performance on college admissions tests that used a multilevel modeling approach, which has many advantages in relation to descriptive or single-level regression-based methodologies that underestimate the effect of the school a student attended on individual performance.

Secondly, the findings of this study have contributed to improve our understanding of the individual characteristics of students that influence their performance on college admissions tests. At the individual level, I confirmed prior studies' findings regarding the scoring gap between female and low-income students and their male and higher-income counterparts (Contreras, Corbalán, & Redondo, 2007; CTA-CRUCH, 2004; 2005). Additionally, I provided strong evidence of the effect of high school GPA and class ranking on students' performance on admissions tests. Prior studies in Chile had only focused on the predictive value of high school GPA of performance in college (Contreras, Gallegos & Meneses, 2009). This study is the first to examine the effect of age on performance on college admissions tests. I found that older students of the cohort score, on average, lower than their younger classmates within their school. Further analyses need to be performed in order to explain the reasons for this phenomenon.

Finally, this study also provided further evidence about the role of schools on performance on admissions tests by quantifying the amount of variance of score that

exists between schools. I found that more than half of the variation in college admissions tests scores is due to the school students attend. In addition, this study has contributed to the existing Chilean body of research by including additional school-level variables that have not been included in prior studies, such as selectivity and college-going culture.

Limitations

This has three main limitations that need to be acknowledged. First, this study focused on a single-year data sample. Therefore, these data provides just a snapshot in time of the way in which student- and school-level variables influence students' performance on college admissions tests.

Secondly, this study focused only at students who actually took the admissions test. Because students self-selected themselves to take the admissions test, there is a self-selection bias might have affected the findings of this study.

Finally, a more technical limitation of this study is that it found heterogeneity of variance at level-1. This is a violation of an assumption needed in hierarchical linear models. This violation may be due to the fact that the datasets used did not provide data on variables that are known to influence performance on college admissions tests, such as having attended a test preparatory course, teacher quality, school resources, principal's leadership, school culture and climate, and parental involvement, among others. Additionally, this heterogeneity may be also due to the decision I made about fixing slopes (individual predictors) that significantly varied across schools. I made this decision because if I had let all slopes to vary across schools, too many schools would have been excluded from the estimation of random effects, as the numbers of schools that had variability to model were too few.

Recommendations for Future Research

Further research should consider different methodological approaches to address the limitations of this study. Future researchers might want to conduct longitudinal analysis of multi-year data. This would allow for the observation of whether the findings of this study have changed over time. Also, other researchers might want to use more sophisticated methodologies, such as structural equation modeling, that allow for the investigation of the structure of relationships among independent variables and the dependent variable that multilevel models alone are not able to model.

Future work should also develop appropriate and reliable measures of variables for which currently there are no available data in Chile. The construction of survey instruments and questionnaires is needed to obtain measures of parental involvement, student engagement, student motivation and effort, student involvement in extracurricular activities, and the like.

This study determined that females score lower than males, and that this gender gap varies significantly across schools. However, the study did not succeed in illuminating school characteristics that explain why some schools have more equitable admissions test score results in terms of gender. Further studies could address the gender gap to determine whether there is a test bias against female students. If this gap actually reflects lower levels of achievement among females, then researchers should be able to find reasons to explain this and to better inform policymakers about ways to reduce this gap.

Another finding of this study that deserves attention in future studies is the effect associated to school and class size. I found that larger schools and larger class sizes positively impact student performance in college admissions tests. This finding is

counterintuitive and actually contradicts prior studies' findings that have found that smaller class and school sizes result in higher levels of achievement (Arzola & Troncoso, 2011). Future studies should examine in more detail the relationship between school and class size and performance.

This study also detected the presence of outlier schools in the data sample. These correspond to schools whose students are, on average, of low socioeconomic status but whose performance in college admissions tests is higher than expected. Future researchers may want to study why students in these schools are outperforming students of similar characteristics and how other schools may learn from their successful experiences.

This study excluded from the sample students from vocational schools. Further studies could focus on the high level of interest among vocational students in taking college admissions tests, even though they themselves opted out of college-track schools. In 2010, 30% of applicants who took the college admissions test graduated from vocational schools (DEMRE, 2011). Therefore, this group of students deserves much more attention from researchers than it has received until now.

I started this study by offering a theoretical framework, the college choice process, to explain the steps students need to take in order to gain access to a selective university in Chile. In doing so, I realized that research about the college choice process of Chilean students is extremely scarce. Therefore, there is much about this process that remains unknown, such as the role occupational and educational aspirations play in Chilean students' decision to attend a vocational or a college track high school, if and how Chilean students use available information about college their search for institutions and programs, the proportion of students that get enrolled in test preparatory courses, the

effect that test coaching has on student performance, the role of financial aid in the choice stage of the process, the influence of parents and teachers in students' pathways to college, why some students that are register to take the test do not take it, what criteria students use to list their application preferences, if and what type students defer their enrollment, and the like. Also, we do not know how different types of students navigate each of the stages of this process and the role that socioeconomic status, gender and schools play in such process. Given the high inequalities of access to higher education in Chile, there is an urgent need to understand the way in which students make decisions about college so policymakers and practitioners can implement appropriate policies and programs to enhance students' educational opportunities.

Appendix A: HLM Output

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com www.ssicentral.com
Module:	HLM2R.EXE (7.00.21103.1002)
Date:	20 February 2012, Monday
Time:	18:24:41

The maximum number of level-1 units = 106414
The maximum number of level-2 units = 1887
The maximum number of iterations = 100
Method of estimation: restricted maximum likelihood
The outcome variable is PSUSCORE

Summary of the model specified

Level-1 Model

$$PSUSCORE_{ij} = \beta_{0j} + \beta_{1j}*(@1990_{ij}) + \beta_{2j}*(@FEMALE_{ij}) + \beta_{3j}*(@MID\_INC_{ij}) + \beta_{4j}*(@HIGH\_IN_{ij}) + \beta_{5j}*(@TOPTEN_{ij}) + \beta_{6j}*(ZGRADES_{ij}) + r_{ij}$$

Level-2 Model

$$\beta_{0j} = \gamma_{00} + \gamma_{01}*(PREF\_SUB_j) + \gamma_{02}*(ADMTEST_j) + \gamma_{03}*(@PRIVATE_j) + \gamma_{04}*(@PRISUB_j) +$$
$$\gamma_{05}*(@MEDIUM_j) + \gamma_{06}*(@LARGE_j) + \gamma_{07}*(@TUITION_j) + \gamma_{08}*(@MID\_INC_j) +$$
$$\gamma_{09}*(@HIGH\_IN_j) + \gamma_{010}*(ZCLASS\_S_j) + \gamma_{011}*(ZPSU\_STU_j) + \gamma_{012}*(ZFEMMEAN_j) +$$
$$\gamma_{013}*(ZGRADES_j) + u_0$$
$$\beta_{1j} = \gamma_{10}$$
$$\beta_{2j} = \gamma_{20} + \gamma_{21}*(ZCLASS\_S_j) + \gamma_{22}*(ZFEMMEAN_j) + u_{2j}$$
$$\beta_{3j} = \gamma_{30}$$
$$\beta_{4j} = \gamma_{40}$$
$$\beta_{5j} = \gamma_{50}$$
$$\beta_{6j} = \gamma_{60} + \gamma_{61}*(@PRIVATE_j) + \gamma_{62}*(@PRISUB_j) + \gamma_{63}*(@MEDIUM_j) + \gamma_{64}*(@LARGE_j)$$
$$+ \gamma_{65}*(ZPSU\_STU_j) + \gamma_{66}*(ZGRADES_j) + u_{6j}$$

@FEMALE ZGRADES have been centered around the group mean.
@1990 @MID_INC @HIGH_IN @TOPTEN have been centered around the grand mean. ZGRADES has been centered around the grand mean.

Final Results - Iteration 26

Iterations stopped due to small change in likelihood function

$\sigma^2 = 2566.82816$

τ

INTRCPT1,β_0	1035.94108	3.27763	9.83318
@FEMALE,β_2	3.27763	55.86609	-9.95576
ZGRADES,β_6	9.83318	-9.95576	51.80595

τ (as correlations)

INTRCPT1,β_0	1.000	0.014	0.042
@FEMALE,β_2	0.014	1.000	-0.185
ZGRADES,β_6	0.042	-0.185	1.000

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.923
@FEMALE,β_2	0.183
ZGRADES,β_6	0.369

Note: The reliability estimates reported above are based on only 1705 of 1887 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.
The value of the log-likelihood function at iteration 26 = -5.720521E+005

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	465.144270	3.684008	126.260	1873	<0.001
PREF_SUB, γ_{01}	-8.374923	1.850811	-4.525	1873	<0.001
ADMTEST, γ_{02}	9.626726	1.870825	5.146	1873	<0.001
@PRIVATE, γ_{03}	55.434501	3.841429	14.431	1873	<0.001
@PRISUB, γ_{04}	9.626265	2.758772	3.489	1873	<0.001
@MEDIUM, γ_{05}	10.416327	2.259767	4.609	1873	<0.001
@LARGE, γ_{06}	26.745685	3.281531	8.150	1873	<0.001
@TUITION, γ_{07}	-11.824909	2.717606	-4.351	1873	<0.001
@MID_INC, γ_{08}	21.766107	2.691053	8.088	1873	<0.001
@HIGH_IN, γ_{09}	46.977941	2.918911	16.094	1873	<0.001
ZCLASS_S, γ_{010}	9.433968	1.186294	7.952	1873	<0.001
ZPSU_STU, γ_{011}	9.393652	1.097031	8.563	1873	<0.001
ZFEMMEAN, γ_{012}	-3.916597	0.794041	-4.932	1873	<0.001
ZGRADES, γ_{013}	52.542230	1.856666	28.299	1873	<0.001
For @1990 slope, β_1					
INTRCPT2, γ_{10}	-9.890312	0.540113	-18.312	100749	<0.001
For @FEMALE slope, β_2					
INTRCPT2, γ_{20}	-30.290479	0.445826	-67.942	1884	<0.001
ZCLASS_S, γ_{21}	1.245827	0.476248	2.616	1884	0.009
ZFEMMEAN, γ_{22}	-2.136150	0.823115	-2.595	1884	0.010
For @MID_INC slope, β_3					
INTRCPT2, γ_{30}	5.398181	0.470729	11.468	100749	<0.001
For @HIGH_IN slope, β_4					
INTRCPT2, γ_{40}	10.620548	0.528224	20.106	100749	<0.001
For @TOPTEN slope, β_5					
INTRCPT2, γ_{50}	10.921217	0.668476	16.337	100749	<0.001
For ZGRADES slope, β_6					
INTRCPT2, γ_{60}	50.775138	0.884580	57.400	1880	<0.001
@PRIVATE, γ_{61}	-2.353973	0.981155	-2.399	1880	0.017
@PRISUB, γ_{62}	-2.697219	0.706120	-3.820	1880	<0.001
@MEDIUM, γ_{63}	2.231107	0.757876	2.944	1880	0.003
@LARGE, γ_{64}	3.372920	0.911689	3.700	1880	<0.001
ZPSU_STU, γ_{65}	4.111031	0.364035	11.293	1880	<0.001
ZGRADES, γ_{66}	8.388696	0.653497	12.837	1880	<0.001

Final estimation of fixed effects (with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	465.144270	3.969512	117.179	1873	<0.001
PREF_SUB, γ_{01}	-8.374923	1.900654	-4.406	1873	<0.001
ADMTEST, γ_{02}	9.626726	1.954720	4.925	1873	<0.001
@PRIVATE, γ_{03}	55.434501	4.179870	13.262	1873	<0.001
@PRISUB, γ_{04}	9.626265	3.404685	2.827	1873	0.005
@MEDIUM, γ_{05}	10.416327	2.252722	4.624	1873	<0.001
@LARGE, γ_{06}	26.745685	3.069673	8.713	1873	<0.001
@TUITION, γ_{07}	-11.824909	3.113104	-3.798	1873	<0.001
@MID_INC, γ_{08}	21.766107	3.063388	7.105	1873	<0.001
@HIGH_IN, γ_{09}	46.977941	3.889685	12.078	1873	<0.001
ZCLASS_S, γ_{010}	9.433968	1.372245	6.875	1873	<0.001
ZPSU_STU, γ_{011}	9.393652	1.236239	7.599	1873	<0.001
ZFEMMEAN, γ_{012}	-3.916597	0.913306	-4.288	1873	<0.001
ZGRADES, γ_{013}	52.542230	2.107399	24.932	1873	<0.001
For @1990 slope, β_1					
INTRCPT2, γ_{10}	-9.890312	0.652857	-15.149	100749	<0.001
For @FEMALE slope, β_2					
INTRCPT2, γ_{20}	-30.290479	0.452718	-66.908	1884	<0.001
ZCLASS_S, γ_{21}	1.245827	0.465893	2.674	1884	0.008
ZFEMMEAN, γ_{22}	-2.136150	0.820144	-2.605	1884	0.009
For @MID_INC slope, β_3					
INTRCPT2, γ_{30}	5.398181	0.495746	10.889	100749	<0.001
For @HIGH_IN slope, β_4					
INTRCPT2, γ_{40}	10.620548	0.538306	19.730	100749	<0.001
For @TOPTEN slope, β_5					
INTRCPT2, γ_{50}	10.921217	0.741123	14.736	100749	<0.001
For ZGRADES slope, β_6					
INTRCPT2, γ_{60}	50.775138	0.955379	53.147	1880	<0.001
@PRIVATE, γ_{61}	-2.353973	1.019848	-2.308	1880	0.021
@PRISUB, γ_{62}	-2.697219	0.758488	-3.556	1880	<0.001
@MEDIUM, γ_{63}	2.231107	0.813317	2.743	1880	0.006
@LARGE, γ_{64}	3.372920	0.932910	3.615	1880	<0.001
ZPSU_STU, γ_{65}	4.111031	0.403516	10.188	1880	<0.001
ZGRADES, γ_{66}	8.388696	0.678052	12.372	1880	<0.001

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	d.f.	χ^2	p-value
INTRCPT1, u_0	32.18604	1035.94108	1691	32302.85659	<0.001
@FEMALE slope, u_2	7.47436	55.86609	1702	2271.35486	<0.001
ZGRADES slope, u_6	7.19764	51.80595	1698	3229.67213	<0.001
level-1, r	50.66387	2566.82816			

Note: The chi-square statistics reported above are based on only 1705 of 1887 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

Statistics for current covariance components model
Deviance = 1144104.150123
Number of estimated parameters = 7

Appendix B: Written Consent for Dataset Use

usach	**Paulina Perez <paulina.perez@usach.cl>**

Solicitud de Base de Datos SIMCE.

1 mensaje

Base de Datos SIMCE <noreplay@simce.cl>	**22 de marzo de 2011 10:10**
Para: "Paulina Pérez Mejías" <paulina.perez@usach.cl>	

Estimado(a) Paulina Pérez Mejías:

Hemos recibido conforme el Formulario de Solicitud de Bases de Datos SIMCE.
Durante los próximos **15** días los archivos solicitados se encontraran disponibles en el link
(http://bases.simce.cl/index.php?id=256). Usando su RUT 12784632-4 y el password 1285871829 , usted podrá descargar directamente las bases de datos.

Instrucciones de descarga:

1. Ingrese su Rut.
2. Ingrese el Código de Solicitud que se le entregó cuando realizó la solicitud y que se indica en este mail.
3. Haga clic sobre el link DESCARGAR de cada uno de los archivos solicitados, y siga las instrucciones de descarga de su navegador.

Atentamente
SIMCE
Unidad de Currículum y Evaluación
Ministerio de Educación

Translation

Dear Paulina Perez Mejias:
We have received your application form to use the SIMCE dataset. During the next 15 days the requested files becoming available on the link
(http://bases.simce.cl/index.php?id=256). Using your ID number and password, you can download the datasets.
Download Instructions:
1. Enter your ID.
2. Enter the application code that came when you made the dataset request and indicated in this mail.
3. Click the DOWNLOAD link for each of the files requested, and follow the download instructions in your browser.

Sincerely,
SIMCE
Curriculum and Evaluation Unit
Ministry of Education

usach   Paulina Perez <paulina.perez@usach.cl>

Datos PAA-PSU
1 mensaje

José Manuel Eguiguren Cosmelli <joselo.eguiguren@gmail.com>   30 de septiembre de 2008
Para: paulina.perez@usach.cl   00:36

Estimado/a: Después de afinar los últimos detalles en la preparación de los archivos han quedado
disponibles las bases de datos de los procesos de admisión a las universidades. A partir del día de
hoy, la aceptación de las solicitudes no tomará más de dos días. En relación con su solicitud previa,
tenemos el agrado de comunicar su aceptación y le adjuntamos las claves respectivas para poder
descargar las bases de datos. Le recordamos leer las condiciones de uso de la información
contenidas en la página web.

Usuario:
Password: ▮▮▮▮▮▮

Atentamente,

Comité Técnico Asesor PSU.

p.d. podrá acceder a los datos desde hoy martes a las 12.00

Translation

Dear Mr./Ms: After adjusting the final details in the preparation of the files, the PSU
datasets are now available . Beginning today, the review of applications will not take
more than two days. In relation to your previous application, we are pleased to inform
you that it has been accepted and attached you will find the respective key to download
the datasets. Please remember to read the terms of use of the information contained on the
website.
User:
Password:
Sincerely,
PSU Technical Advisory Committee.
P. S. You can access data from today Tuesday at 12.00

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