THE ROLE OF ENGINEERING SKILLS IN DEVELOPMENT

By

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for my mother
and for her mother

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CHAPTER I

THE DEVELOPMENT OF AN ENGINEER

Introduction

A young child dreams of being an astronaut. She dreams of piloting a complex rocket full of buttons and gadgets through the sky and discovering new planets in the unknown, unchartered universe of scientific frontiers. As the child grows, she makes her way through the sacred halls of formal schooling. She takes classes, goes to college, and starts to work. Somewhere along this way, the stars and spaceship dreams of her childhood become obscured, maybe by the ceiling of an unsupportive classroom, maybe by the bright lights of other opportunities. More likely than not, when we see the adult, the starry-eyed engineer is no longer there. Where did she go?

In this dissertation, I examine the formal mechanisms that create qualified engineers. I am motivated by the important role that engineers play in the economic and social development of nations around the world. I am further motivated by the justice and importance of supporting children from all backgrounds in their aspirations to become engineers. I use quantitative and qualitative analyses to understand the factors that influence engineering achievement and application. I focus on college factors, and I extend the central analysis with studies of pre-college problem-solving achievement and post-college choice. A broader understanding of the engineering training process as a whole gives policymakers a more nuanced, detailed understanding of where to target solutions as well as an increased understanding of areas that previously posed challenges in research design and analysis.

The Engineering Pipeline

The chronology of formal engineering training is often described as a pipeline (e.g., National Science Foundation, 1987), one that runs from the student's birthplace, into pre-school acculturation in the home, through mandatory primary and secondary schooling, up to formal engineering training in college, and finally leading to engineering practice in the labor market. This pipeline is leaking. Policymakers are worried. Who will build the society of tomorrow, and, more urgently, who will fix the society of today?

Engineering knowledge is vital to the development and sustainability of industrialized economies. The National Academy of Engineering describes how the most pressing challenges of the day—for example, making solar energy economical or securing cyberspace—require engineers to lead in their solution (National Academy of Engineering, 2010). This dissertation examines three major points at which the pipeline is losing engineers. Further, I examine the identity of the engineer who either persists through or stops out of the engineering training process. I divide the turning points in the engineering pipeline into two categories: obstacles to continuation within the pipeline and outside alternatives that draw potential engineers into other fields. Why is this important conduit of human capital leaking? And for whom?

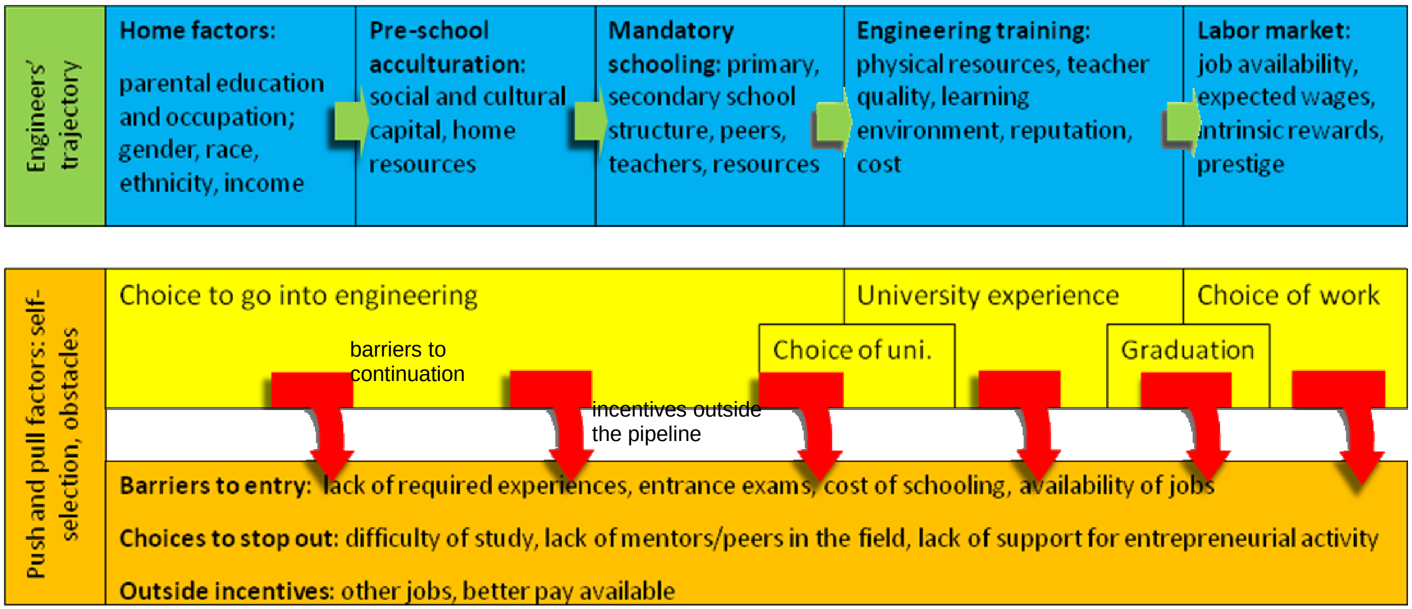

Figure 1. The Engineering Pipeline

Figure 1 details the course of the engineering pipeline. Engineers' trajectories start from the earliest moments—in the home—where they begin with the personal characteristics of their birth (e.g., gender, race/ethnicity). They are then exposed to social and cultural experiences in their home and their community. They move into required formal schooling, where they, along with their peer group are exposed to the particular resources and practices of that school. Up until this point, they have begun the decision-making process that leads to their choice to study engineering in university. After primary and secondary school, they make the additional decision of the university they attend. Once in university, they are provided with a set of resources and experiences particular to that institution. They make the decision to stay in the program, and they also make the decision to complete their undergraduate degree. Finally, they choose to enter the labor market in a certain sector.

At each turning point, engineers are faced with choices—both in persisting or exiting the pipeline as well as in their choice of major/sector of engineering. They are also faced with obstacles and competing alternatives to their continuation—barriers and leaks in the system. The obstacles and alternatives presented to each engineer differ greatly. A number of factors go into the engineer's decision-making process, but one of the most important is her accumulation of technological capital.

I argue that technological capital, its acquisition, and its application are actually new components of contemporary cultural capital. In this introduction, I first define technological capital and how it fits within the established frameworks of social and cultural capital. I then discuss each of the important components illustrated in the pipeline diagram to understand how earlier works on social and cultural capital inform this model. I begin with the first components of the pipeline: home factors and pre-school acculturation. I present ways in which seminal social and cultural capital work informs the relationship between out-of-school factors and in-school opportunities. I then discuss the ways in which mandatory schooling and engineering training further constrain the opportunities of students. I describe the reproduction mechanisms of selection into higher levels of education and the social and cultural capital components that moderate selection. Next, I proceed to discuss the more specific tracks that engineers might choose, citing literature on tracking and its relationship to social and cultural background. Finally, I discuss the differential outcomes that engineers going through this "pipeline" encounter. I describe broad frameworks for human development. I conclude this chapter by describing the structure and contribution of the rest of the dissertation.

Technological Capital

I begin by defining technological capital and justifying its distinction from other forms of cultural capital. In this dissertation, I extend cultural capital to include the newer dimension of "technological capital". Technological capital consists of both the understanding of digital tools as well as how these tools are applied. For example, technological capital includes the types of phones that different groups of people view as normal or acceptable. Low-income Americans make up the majority of the user population for pre-paid cellular phones, while post-paid plan users have higher incomes overall (Sullivan, 2011).

Technological capital, its acquisition, and its use all exhibit the same characteristics as other components of cultural capital. Technological capital comes with a certain lexicon, words to indicate one's knowledge of objects in the area, similar to the valuation of certain types of art or leisure activities (Bourdieu, 1977). It comes with a specific history, an understanding of a constructed hierarchy of types of technology, uses of technology, and pressure for the most recent technological tool. With an understanding of the technologies that should be valued, one can gain entry into more privileged social circles.

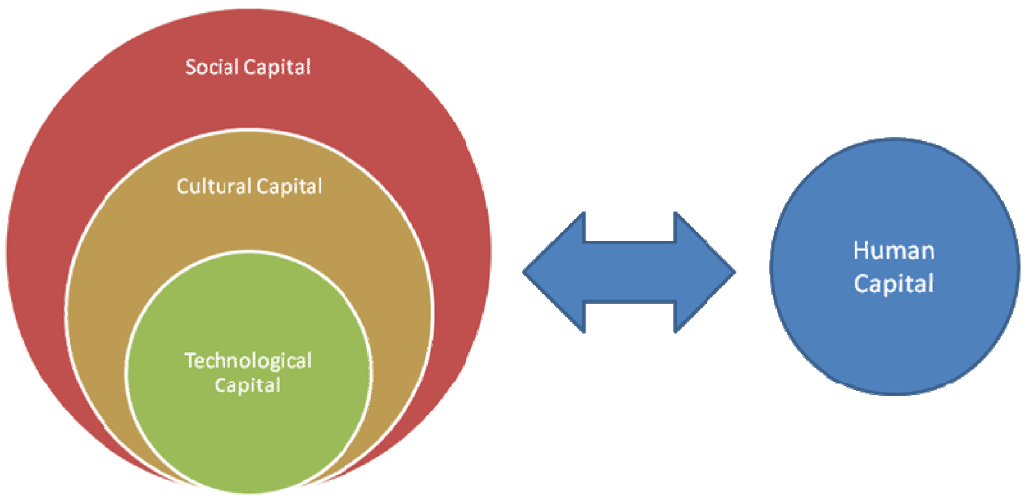

Figure 2. Technological Capital as a Component of Cultural Capital

Certain technologies received more valued status in society at large, though their valuation is often unrelated to their efficacy, arbitrarily constructed as more- or less-privileged groups espouse given technologies en masse. The school system is then set up to reward certain types of technology use and awareness. For example, while schools attended by more privileged groups may inculcate a respect for the fields of engineering and hard sciences, schools attended by less privileged groups may focus more on vocational technical work as a valued profession. While more privileged schools may invest in curricula that ask students to use technology to search for information at home, less privileged schools may only present computers as places for free-time game use. (I base these subject-specific hypotheses on general findings of differences in curricula between schools by Anyon [2008], which I describe further below.)

As with other forms of cultural capital, technological capital intersects with the dimensions of race, class, gender, culture, and age. Social capital broadly includes both the connections between members of a specific group (bonding capital) and the links to other groups in the larger society (bridging capital); communities create both bonding and bridging capital in the dimension of technological capital as well (Coleman, 1988). Within a community, certain types of technology and careers that employ technology are valued. For example, a given community may contain numerous role models who work in engineering. Members of the community may underscore the value of an engineering career and the importance of studying science, math, and technology. Other communities may not.

The capacity to own and demonstrate use of prized technology signals an individual's possession of valued technological capital. Technological capital is a new addition to the dimensions of cultural capital; it is distinct from linguistic cultural capital as it is both a language as well as a physical and conceptual resource and an avenue to information. I use it here to refer specifically to engineering and information and communication technologies, often digital today.

Home and Community: the Beginning of the Pipeline

Before a student even enters a school, the engineering pipeline begins in the home. I begin here as well, incorporating important social and cultural capital frameworks that describe the reproduction of social and economic hierarchies stemming from a student's home environment. The course that a student follows later in life derives from early exposure to elements of class and culture, career aspirations and educational motivation, and norms and practices in her home. Early work by Bowles and Gintis (1976), based on earlier work of Marx and Weber, laid the groundwork for the ideas of cultural capital and habitus, describing the way the needs of an industrial economy create a hierarchical system with differentiated jobs that must be filled. The hierarchies mimicked by schools condition students both to be prepared for and to accept the same status jobs that their parents have in the industrial economy. The structure of society is reproduced via the school system. The general knowledge, behavior, and skills are passed from one generation within a social group/class to the next, so children, by virtue of birth, are provided with distinct stocks. Schools, as institutions of the community and controlled by the dominant classes, tend to systematically favor the capital possessed by these same dominant classes and devalue that of the less-privileged. Schools put a value on background factors, and these are converted into "objective" currencies such as jobs, achievement, and salaries.

Specifically, the example of language illustrates how a student's background translates into commodifiable resources (Bernstein & Heath, as cited in MacLeod, 1995). The authors note that membership in different social milieus generates distinct vocabulary and speech patterns through socialization. This linguistic cultural capital becomes an enabler or an impediment in school, where certain cultural resources are valued, and only some children may actually have the resources that are being measured.

Collins (1977) lays out a theory of conflict, drawing on Weber (and Marx) to describe how culturally distinguished groups struggle for an advantage for various goods. Collins proceeds to describe how education serves the purpose of teaching to particular groups. Individuals are “allocated” to these groups by institutions, often through schools (Meyer, 1977). These schools may be put in place by implicit or even explicit purposes of cultural and social control; for example, Rogoff (2003) describes the relationship between cultures of schooling and their purposes in how Western schools were used as foreign missions, colonializing tools, and supports for American expansion. On the other hand, tailoring schools to target the local context may be the most efficient; Miller and Shinn (2005) describe the utility that policy interventions can gain from building on indigenous knowledge. The relationship of in-school learning to home background is visible in science education as well. Children in a rural Mexican community, for example, share core sets of community knowledge related to plants (Wyndham, 2010). The knowledge that students begin to accrue and value in the home translates to the capital they bring with them through later steps in the engineering pipeline. I note this in my studies by focusing on the environments in which students access technological resources and noting the predictive power of their background factors.

Social capital—as conceptualized by obligations and expectations, information channels, and social norms—is a resource for actions on the part of the student, whether individually, within the family, or within the community. Coleman (1988) expounds on the relationship between social capital, other forms of capital, and the other people with whom high school dropouts interact. The student's decisions are an amalgam of individual "rational actor" choices and accepted directions within the social context. The decision-making process as it relates to the engineering pipeline is described further below. The idea of the social context extends to an understanding of space and place as important determinants of students' opportunities. Lareau (2003) looks at the very different day-to-day lives of children living in close proximity, but different neighborhoods, from each other. These children experience their respective locales very differently, and their interactions with school are starkly contrasted.

These interactions are characterized by the cultural capital that students *display*, the markers they show to indicate their group membership and the resources (including technological capital) that they possess. The idea of "habitus" describes how a student's "natural" behavior translates into accessibility of resources. Bourdieu (1977) describes how children of different classes inherit vastly different stocks of cultural capital. These children come to school with different "habitus" resources, systems of "lasting, transposable dispositions which, integrating past experiences, [function] at every moment as a matrix of perceptions, appreciations, and actions" (Macleod, 1995, p. 14). Implicit biases, whether or not they are founded, leads to administrators, teachers, and others in power to reward students differentially. In a more recent example, researchers find that math teachers are consistently biased against female students (Riegle-Crumb & Humphries, 2012). This applies to the understanding of technology and its application that I investigate in my dissertation. I find support for the theoretical frameworks of social reproduction, that students who come from different backgrounds, even when exposed to the same resources, understand and appreciate technological tools in different ways. The root of the engineering pipeline—the home and the community—is the source of many of differences that we see further down the line.

We want to learn. We crave new information, novel stimulation for our neurons. Universally, people want to feed their brains, advance their careers, and use knowledge to create stable lives for themselves and their families. And yet, we cannot escape the nature of the jungle around us. Complex differences in political structures, cultural norms, geographical characteristics, and economic backgrounds incubate together to create challenges and opportunities unique to our individual situations. As students apply the technological capital and other resources that they have amassed, they move in different ways through the educational system. I focus on the background characteristics of gender, race, and socioeconomic class as important determinants of engineering educational opportunity and achievement.

Next in the Pipeline: Mandatory Schooling and the Beginning of Selection

After growing up in a given community and beginning to understand the world through their own unique lens, students enter the formal education component of the engineering pipeline. There, a series of selection processes direct them into various sectors of schooling. This selection is not entirely random. One of the most problematic challenges in empirical investigations of returns to educational inputs is the fact that different types of students systematically choose different schools, programs, and careers. The process of selection happens multiple times throughout the pipeline, and it is done by institutions and policymakers as well as the students. There is a self-selection process in the choices students make, and, often, there is a "creaming" of the student pool with groups that are seen as having the highest potential allowed to move on to the next level of education. I detail further here the theoretical work in social capital and development economics that describes how both the individual and the society selects the students who will continue on in the engineering pipeline and those who will not advance.

The technical-functional theoretical perspective offers that, in an industrialized society, schools serve as an efficient apportioning tool. The skills required of workers are met by their educational training. Educational requirements are constantly increasing as the skills required for jobs increases (Collins, 1977). A more progressive view, though, argues that education merely serves to justify the stratifications already extant in society (see above). Meyer's work (1977) puts forth numerous propositions illustrating how schools are used to allocate students to different social groups; many of these allocation mechanisms are less related to providing freedom of choice to the individual or to answering the diverse needs of a society than they are to reproducing previous structures of power.

From a societal (or policymaking) perspective, education can be used as a way of controlling the human capital necessary for their economies—if more engineers of a certain type are needed, educational planning can deliver these workers. Orazem and King (2008) detail a basic economic cost-benefit supply-demand model for local and central government policymakers. The authors describe an equilibrium model incorporating a supply of spots in schools and a demand by households for schooling (based on price, household income, and wages the child would earn at that time). This model describes how and where governments might decide to subsidize schooling or limit access. Private schools, for example, or vouchers, may be tools for policymakers to create structures promoting or hampering access or career direction. And, as investigated in my dissertation, selection into public or private schools is an important mechanism by which the engineering pipeline is segregated. Given the link between household income and school attendance, governments may increase household resources to increase educational access (in practice, often with conditions, e.g., *Progresa* [Schultz, 2004]). This example is one that attempts to tailor itself to the context, focusing on the opportunity cost in rural areas and allocating more money to girls, and, as a result, changing the household decisionmaking process to alleviate barriers to access.

The education decision-making process is not one-sided; policymakers may shape the demand for certain skills, but students and families form the supply of students and graduates. The needs and desires of policymakers may not always align with those of households or individuals, and, further, policy interventions may not always have the intended consequences. For example, while increasing enrollment has characterized an achievement of increased access, there has not been a commensurate increase in skills achievement, though governments increasingly want higher skilled workers (Orazem & King, 2008).

The decisions of students and their families are just as complex as those made by policymakers. Based on a traditional household model of decision-making regarding human capital investments, I look at the decisions an individual makes as she goes through the formal schooling component of the engineering pipeline. Orazem and King (2008) describe benefits to schooling in terms of anticipated future earnings (discounted at a rate that depends on the family's income), a function here of years of schooling and exogenous factors related to schooling outcomes (e.g., ability, school quality). This depends on how useful a child's time is in the home versus in school (and in the future if more educated) and on the quality and quantity of school supply. Further, girls' time is often more valuable in the home in rural, developing contexts, and their human capital may be discounted by their parents relative to boys' learning.

Perceived costs to schooling may include explicit costs such as tuition, uniforms, and other inputs, as well as fixed opportunity costs such as current foregone earnings. Context-specific considerations, such as the average amount of schooling, preclude or change decisions for students from certain milieus—e.g., in some contexts, it may be significant if a child EVER attends school. Investment in human capital may change based on the knowledge that an educated student may emigrate; considering mobility from a household perspective, rural households may under-invest in education because the external benefits of educated rural children are transferred to urban areas instead of their home locales (Orazem & King, 2008). Parents' and students' access to information (Stanton-Salazar & Dornbusch, 1995), peer behavior (Tierney & Venegas, 2006), role models and learned role confidence (Cech et al., 2011), and risk aversion (Duflo, 2006; Perna, 2006) all combine to determine selection into further schooling. In most cases, this means that traditionally underserved groups—low-income, racial/ethnic minorities, and women—systematically select out of persisting through the engineering pipeline at higher rates.

Anyon's research underscores the fact that school selection practices are unequal in relation to out-of-school factors, as school knowledge and class are closely related; students in schools that serve working class families receive different content in a different format from students in schools that serve professional or elite families (Anyon, 2008). Meyer describes numerous ways in which schools use their structures to allocate people to unequal outcomes in social status groups (Meyer, 1977). Anyon (2008) further describes how schools can be tailored, but in a perversely stratifying way, whereby students receive different curricula (as noted before in an example regarding technological capital) and have different behavior demonstrated to them depending on their SES. The selection barrier, even during mandatory primary and secondary education, is one way that the pipeline is broken, and I illustrate how this barrier disproportionately affects students with less-valued technological capital.

The Crux of the Pipeline: Engineering Training and Differentiation

The core of engineering training is usually seen as the undergraduate degree experience. Here, students are further tracked into schools and more specifically into disciplines of engineering. Formal "tracking systems" are another reason the pipeline is has a multitude of problems. Students do not completely have free rein to choose the education they receive. Entrance into different levels of schooling, types of schools, and programs of study are often based on entrance exams, prior training, or other qualifications (e.g., Brazil's *ENEM*; Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira, 2012). Further, students who are traditionally disadvantaged find themselves disproportionately less likely to enroll or persist through college, and, further, to enroll or persist in higher-reward tracks (e.g., Stanton-Salazar & Dornbusch, 1995; Perna & Titus, 2005). Major works in social reproduction theory in the previous section describe how students from different backgrounds are differentially prepared to access higher levels of schooling overall. In this section, I further detail how this selection mechanism works even within disciplines or within the same schools ; the mechanism of tracking and differentiation between more- or less-valued types of engineering provides inequitable access to more-valued technological capital.

Social establishments are created to serve the members of the community. The institution of the formal public school is often burdened with the purpose of providing an equal learning platform to all and serving as a social equalizer; the movement for universal primary education (e.g., the United Nations Educational, Scientific, and Cultural Organization [UNESCO]'s Education for All) pushes for a country's formal public school as providing a basic right across the nation. However, some scholars argue that as one of the first, most formative social institutions that nearly all inhabitants will encounter, formal schools actually serve to exacerbate and solidify the inequalities already present in society. While policymakers may portray this as an "apportioning" function of schools, which provide differentiated labor for a diversified economy, tracking inequitably distributes students within schools and within areas of study that are hierarchically rewarded.

Processes and pedagogies such as tracking within schools have been shown to have notable effects on student achievement (Gamoran & Berends, 1987). Further, even within the same schools, the techniques devoted to children of different backgrounds differ vastly, and the experiences that students have are, on average, quite different (Jencks & Phillips, 1998). Scholars continue to debate the structure and consequences of this phenomenon (Hallinan & Oakes, 1994). Students of different backgrounds are represented disproportionately in different academic tracks (Kelly, 2008). Gamoran (2004) shows that these tracks receive different content, which, especially for disciplines like math which build on prior knowledge, makes catching up difficult; what is more, teacher quality measures show that the more experienced teachers are seen as necessary for the more advanced tracks.

One of the most common ways of tracking in engineering is structural, between-school tracking for academic and vocational studies; this type of tracking is especially relevant for engineering and technical studies. The debate between vocational and academic training has been long and contentious (e.g., Foster, 1965; Psacharopolous, 1987). Many bodies recognize the need for higher education opportunities to be diverse (e.g., Task Force on Higher Education and Society, 2004). Indeed, arguments over financing higher education through rates of return analysis contend that allowing general education or individual choice results in an overabundance of graduates in the wrong fields (Psacharopoulos, 1986). Such arguments justify the need for government intervention to actually promote tracking.

Economic analyses (Psacharopoulos, 1987) further argue that the individual returns to vocational education outweigh its public costs, since vocational education tends to be more expensive due to financing for equipment and infrastructure. Debate then becomes even more complicated as policymakers look to private financing for vocational education, though it is more often the case that low-SES students are tracked here (Bennell, 1996).

Even decades ago (Foster, 1965), international policymakers pointed out that, given the agricultural nature of less-developed areas, broad access to vocational and technical education would be important, perhaps more beneficial even than academic training. Technical and vocational education (TVE) provides immediately-marketable skills, and these practical fields may be directly applicable to infrastructural development needs. While tracking may serve as an apportioning tool, having multiple tracks within engineering does allow for diverse alternatives from which students can choose their own path. However, the way that tracks are rigidly stratified places limitations on students going through the engineering pipeline.

Even early scholars (Foster, 1965) pointed out that some variables were missing from this kind of analysis. Students of TVE (technical and vocational education) would not be flexible and prepared for a shifting labor market; the fields of TVE would have to match quite well with job needs; and the populations accessing TVE might perpetuate social inequalities. And, vocational and academic education need not be seen as direct substitutes, as both have social benefits. More recently, some point out that skills and information possession in the modern "knowledge economy" are a currency in and of themselves. The tracking mechanisms of the engineering degree channel the flow of engineers through the pipeline into different opportunities; more lucrative opportunities are disproportionately offered to students who have more of the traditionally-valued technological capital.

Entering the Labor Market: Engineering, Technology, and Development

Finally, the engineer has reached "certification" status and is ready to enter the labor market. Policymakers are increasingly concerned with concerned with which students will reach this point and where engineering students will enter the labor market—the final step in the engineering pipeline. In particular, policymakers in low-income contexts are concerned about graduates who will emigrate. Increased schooling may allow students more freedom in mobility (Orazem and King, 2008), and central government oversight of local education may be useful to the source country because of increased intra- and inter-country migration. Interregional migration may have public benefits (Schultz, 1964; Saxenian, 2005), but more often, policymakers are worried about the flight of human capital from the home country.

For students making study and career decisions, some factors weigh more heavily in the decisionmaking process than others. Harren (1979) creates a career decision-making model which divides the "process" of choosing a major into distinct areas: awareness, planning, commitment, and implementation. In my study, I ask students about their perceptions in these different stages, as well as their aspirations. Studies that have polled students about the factors they considered when choosing an engineering major show that financial considerations are often cited, and a "match with interests" may be the most important (Beggs, Bantham, & Taylor, 2008), which I include in my survey. I use student perceptions and ask about individual factors as well as perceptions of broader factors.

Decision-making processes differ by SES, and the starkest contrast can be seen for students living at the margins of poverty. Duflo (2006) describes the decision-making process of the poor as adhering to an appropriate rationale to which classical economic theory is not applicable. Banerjee and Duflo (2007) summarize household surveys in a number of contexts to describe "the way the extremely poor live their lives" (p. 141), illustrating the ways in which this descisionmaking process differs from the rational actor model normally applied in previous studies of student choice. This has important implications for engineering and technology, as the most beneficial technological training may not always be chosen by the students who could most benefit from it.

Lou (2011) provides an empirical example of the decision-making process for students from a village background. She investigates how rural students navigate the decision to leave (or not) their home for the appeal of the city. In her ethnography, she looks at how rural students view their own locales as industrialization takes place in the towns and cities nearby. Leaving for “the city” is “romanticized” as opposed to the “polluted”, corrupt countryside, and schooling is seen as the path there. However, a competing perspective sees schools as a place of huge academic pressure that is not completely delivering on the students’ hopes, and more students are dropping out. For whom is schooling providing opportunities? Who can access development?

At the national level, the engineering pipeline is a key component of development and sustained growth. And, at the individual level, information and communication technology (ICT) has become a type of cultural capital; in addition, a student's capacity to enter the engineering labor market at an advantageous point is also a component of technological capital. Both the possession and use of technological capital are part of Sen’s concept of capabilities and an individual’s own freedom. Sen defines “capabilities” as the combinations of functionings accessible to a person, the life they can choose for themselves. The “capabilities set” is the group of functionings a person can choose from (Sen, 1999). Given the importance of technological capital for nations and individuals, it is imperative that policymakers understand whether the investments made in formal university training are well-directed, and whether policy changes directed at pre-college factors and post-college decision-making can help to address the lack of engineering capital. I detail below the three studies that provide novel insights into the engineering training pipeline for students from less privileged backgrounds.

Analysis

Technology on Trial: Can Computers Effectively Increase the Engineering Skills of Traditionally Under-served Populations?

Since the middle of the twentieth century, computers and learning have been enthusiastically linked, with bright hopes for a world-changing technology to cure the ailments of the brick-and-mortar education system. New learning technologies are seen as specifically useful for teaching basic engineering skills such as critical thinking or problem solving. LOGO, Number Munchers, Math Rabbit—each decade has seen its share of computer-assisted learning (CAL) programs heralded as system-altering tools, and each decade has seen them subsequently added to the tally of interventions past. Since the 1980s, educational computing in low-income areas in particular has been promoted as an assured new digital fix for the learning and "21st century preparation" of traditionally-underserved groups. Unfortunately, the revolution has not happened. In practice, digital "fads" have frequently failed. And, in evaluations, researchers have not conclusively measured the utility of computers for the engineering education of underserved students.

But now, technologies have changed. Computer penetration in low-income areas, the flexibility of software, and the spaces in which computers are available argue more today than ever for the potential of CAL. Better data are available to estimate the impact of computer use on engineering achievement. And, advancements in statistical methods for causal inference make it possible to use newer secondary data to clearly understand the impact of computers. A new look may reveal more conclusive evidence for technology as a tool to train pre-college engineers.

I use information from the Programme for International Student Assessment (PISA) to model the relationship between independent and school-based student computer use and problem-solving outcomes within and between schools and countries. The overall question I seek to answer is: how is computer use related to problem-solving skills? What relationships exist for independent and school-based use, and how do these types of use interact? Does this relationship vary across schools and countries? Does this relationship vary across types of use, and do results persist across assessments?

I address selection issues inherent in this cross-sectional dataset by matching students on family and household resource characteristics to move closer to measuring the causal effect of computer use and engineering skills. I use a generalized propensity score and a matching estimator to estimate the average treatment on the treated (ATT) effect. To understand the utility of technology as a support in low-income contexts, I focus on a varied set of high-, middle-, and low-income countries included in PISA's dataset. I also separate out students who use computers in low-income households and match them to similar non-users who also come from low-income households.

I find evidence that previous work has neglected to investigate a crucial dimension of social and cultural capital in human development: technological capital. This study comes to three conclusions: school use of computers has a positive effect on problem-solving achievement in the two large, diverse, high-income countries studied; home use has no effect or a negative effect; and use "elsewhere" is positive at low levels of use. These imply changes of policies in the following three ways: schools outside the US and Canada could look at the programmatic practices and environment for school-based computer use in these countries; opportunities for more “effective” home use should be supported, e.g., increased parent information on educational computer use; and, use “elsewhere” should be both encouraged and facilitated at moderate levels. As a tool often implemented to begin the fundamental problem-solving training of engineers for the modern “knowledge economy”, computers are promising interventions that still need fine-tuning.

What Can College Do?: Social, Cultural, and Technological Capital in Brazilian Higher Education

Engineers are sought after as the catalysts for nations' economic sustenance and growth. However, there is little conclusive evidence as to what educational inputs are directly connected to training better engineers. Indeed, there is little data at the college level in any country, including the United States, to explain what colleges do to effectively increase the achievement of graduates in any field. Recent advances in nation-wide university assessments in Brazil offer a way to concretely answer the question plaguing national policymakers worldwide—what should universities invest in to create essential human capital for a competitive global knowledge economy?

The most important advancement in the field of higher education policy analysis is the growth in the availability of data on student performance at the college level. The first national-scale dataset of this sort come from Brazil; it gathers nationally representative information and includes a general and subject-specific knowledge assessment. I use these data here, in one of the first quantitative studies to provide estimates for the predictors of student achievement at the college level. I exploit the capacity of the national dataset from 2005 and 2008, using student- and institution-level background factors for a representative sample of students graduating from undergraduate engineering degree programs.

Are the investments in costly engineering college inputs paying off? Do the inequities observed in primary and secondary education persist for the limited group that makes it to tertiary schooling? I find that individual characteristics such as race and gender have strong predictive power for a student's score (especially on the engineering test), for what type of university a student attends, and for whether that student finishes the degree. A student's home environment and the schooling she was exposed to before college also predict her score, even within institutions. However, university factors also matter—there is growth from first to final year, and factors such as large classes and reports of bad teachers are related to lower scores. The environment for research and the types of peers one has at university contribute to student success.

These findings imply that expanding opportunities for high-quality (private) high school across races and income levels and improving the state of public high schools could have benefits into the college years. On the flip side, interventions to support faculty development in private universities could raise the achievement of students who are tracked into these schools, but expanding access and opportunities in the public higher education system may be an even more promising intervention.

In my analysis, I make two unique contributions to higher education policy analysis. First, I look at predictors of performance on a national, standardized assessment in two different sets of cohorts. Second, I use detailed individual background information to conduct checks of consistency of my results. Education policymakers tend to view university as a separate world, a specialized place—a place where students are no longer children and a time when students become adults and knowledge acquisition becomes job preparation. My work applies analyses that have uncovered fundamental tenets of the understanding of pre-college education and finds that the university is largely an extension of the pre-college experience.

The ENADE scores, along with measures of the university resources, are used in the "General Index of Courses", a national evaluation system. However, my work illustrates the need for an understanding of how efficiently these resources are used, as there are significant differences between institutions in the resources they have available. Engineering companies in Brazil often only look at graduates from a few of the top universities.

Even among similarly-selected peers, coming from a background where students have been exposed to the utility of formal schooling (parent education) and academic norms and effort (reported study time), students in higher education are better able to make use of the same resources to learn how to apply knowledge to technical problem solving. But further exposure to technological resources in higher education matters as well. It is not the physical resources themselves; for example, the area of the laboratories at the school does not predict higher achievement. It is being in an environment that values them, being exposed to an innovative, research-valuing, practical-oriented learning space; practical work and research emphasis were both strong predictors of achievement. The acquisition and application of job-related technological capital depends on both the home and the learning environment. Opportunities that recognize the intersection of the two and broaden opportunities are vital for national development.

Houses of BRICKS: Career Decision-making for Engineers in Growing Economies

Engineers are seen as a vital pillar for the construction of a healthy, industrialized economy. However, they are also seen as a threatened, scarce resource, one that is expensive to create and difficult to pin down once it enters the labor market as a highly-desirable asset. Low- and middle-income countries in particular are concerned that they lack engineers they need to support the growth of local industry, the expansion of infrastructure, and the improvement of living standards.

I investigate the pivotal point in the engineering pipeline where the engineers who have successfully reached "certification status" and are completing their undergraduate degrees and preparing to enter the job market. I ask final year engineering students in exemplary institutions in South Africa to describe their concept of the "local" and "global" space and then to express the push/pull factors that exist in each and affect their decision-making process.

I find that students note an emphasis on global preparation compared to locally-relevant topics, an under-preparation in relevant real-world skills compared to their importance, and a need for local engineers. This implies the following policy recommendations. Starting in primary school, locally-relevant engineering and the value of working in it could both enhance student learning and prepare them to enter the field later in their educational careers. Practical courses with local hands-on experiences within the college curriculum could also serve the dual purpose of enhancing learning outcomes and connecting students to the local space. Finally, incentives to return once abroad (e.g., scholarship that requires returning to South Africa) or to go into engineering entrepreneurship could provide both private and social benefits.

The motivation is not lacking—engineers are already an intrinsically-motivated group. Many report that the challenge of completing engineering degree itself was part of the appeal of the major. Despite this passion, students do not interpret the local need for engineers as applicable to themselves. Barriers to local application of engineering training need to be lifted, and (even small) bits of encouragement to practice engineering locally should be in place.

Contribution

This dissertation makes novel contributions in four areas. First, it asks questions that are prevalent in the policy conversation, but it asks them about and, in fact, focuses on populations that are left out of the bulk of research studies. Second, it analyzes data that have barely been touched and gathers new data where information was previously nonexistent. Third, it demonstrates and begins to expand upon a new theoretical concept. Finally, it provides useful recommendations for policymakers that open up new directions to support important fixes for the engineering training pipeline.

Context

The use and development of engineering ability is a prescient, pressing policy question. However, whether the question is about how technology tools can help engineers learn, or how engineering colleges should work, or how engineers are needed to fill important jobs, the issue is frequently framed in broad terms, looking at average effects across many different groups of engineers with vastly different experiences. Administrators call for the expansion of technology in schools or recruitment into "STEM" fields, but they pay less attention to *who* is being trained. In my study, I explicitly focus on the relevance of a student's identity to the opportunities she receives. The cultural context of engineering education is a novel addition that I offer here.

Data

The central analysis in my dissertation estimates the importance of school and non-school factors in educational achievement at the higher education level. To do so, I employ a large, novel dataset that has been used previously only a handful of times. The information gathered in this student-level dataset is powerful, but this dissertation is one of the first to fully exploit it.

Not only do I perform analyses on a recent dataset that has rarely been studied before, but I gather new information. I gather information from the perspective of the students who are going through the engineering training process. A major piece of the pipeline puzzle that has been missing is the knowledge of what happens to the students after they receive their degrees and the understanding of why students navigate the schooling process in the ways that they do. This study provides important steps in illuminating this issue.

Theory

By incorporating new information and focusing my study on the novel context of students' identities, I am able to make contributions to a new area of theory. The theoretical frameworks of social and cultural capital form important supports for many analyses. However, technological capital as a component of cultural capital is an important new area of theoretical development. The possession of technological capital promotes or prevents access to future opportunities. It is the new cultural key to the more revered doors of upward mobility. In this dissertation, I illustrate how the role of technological capital plays out in the creation of human capital.

Policy

These issues are important to connect to policy changes. I make suggestions that are immediately useful for implementation. Recommendations are frequently made to "tailor" education, but less work has been done to try to understand the factors that are important to tailor learning to and how this can be done more effectively. How do people learn in different environments? How do you get people to stay and focus on their own communities? How do people stay connected with home while navigating educational pipelines? Is it peers? Family? Neighborhoods? Schools? What factors are important to tailor learning to? New developments in digital technology and engineering hold promise for underserved communities. But, without an understanding of how technological capital is acquired and applied, policymakers may be investing in expensive inputs without benefits to the students or the community. The removal of obstacles and the addition of incentives in the decision-making process would help all students to navigate the engineering education process.

CHAPTER II

TECHNOLOGY ON TRIAL:
IN WHAT ENVIRONMENTS CAN COMPUTERS EFFECTIVELY INCREASE THE ENGINEERING SKILLS OF TRADITIONALLY UNDER-SERVED POPULATIONS?

Policy Imperative: Another "World-changing" Invention?

In 1947, U.S. Chairman of the Federal Communications Commission Charles R. Denny described a new technology: "Its educational potential is unlimited. It will be the most powerful communication tool of them all" (Wolters, 1947, p. 1). Sixty-five years ago, he was describing the television, which was supposed to radically transform the essence of learning.

Subsequent classroom technologies have been consistently welcomed as the next silver bullet for the challenges of training young technologists. The same language extolling the utility of the TV could be inserted into an article about computer-based learning today, as educational technology continues riding the waves of public opinion. Beyond the name of the technology, little seems to change, and yet computer-based learning interventions today receive the same faddish fawning, faith, and finances. They are bandied about in the popular press (*New York Times*, 2010; *Times of India*, 2010); significant government funds are invested in their implementation (e.g., 100% of Singapore high schools on internet, student-computer ratio of 8:1; Twining, 2002); and the educational technology industry commands huge monetary resources (e.g., $16 billion in the USA; McCrummen, 2010). This significant investment of capital despite mixed reports of computers' utility is enough to warrant a more rigorous evaluation.

But, there may be even more reason to reexamine the utility of computers in different learning environments now. The unique flexibility and interactivity of computer-aided instruction may actually distinguish this intervention from previous technologies—whether books, assessments, or copying machines. Given the widespread nature of computers—there are nearly two billion internet users worldwide (Internet World Stats, 2010)—and its peculiarities (e.g., tailoring to the user, Dahotre et al., 2011), computers may lend themselves to breaking through the disappointments of technologies past. The accessibility and structure of computers now may adhere more closely than ever to a theory of change for imparting basic engineering skills such as critical thinking and problem-solving. Further, new data and statistical tools may aid in the detection of the effects of computer use on achievement.

This study is motivated both by the dire need for evaluation of a broadly-implemented tool and by the educational potential this tool may have. The perceived importance of computer-based learning interventions in training innovators, especially in resource-challenged contexts (see, for example, the World Bank's promotion; World Bank, 2011), demands a deeper knowledge base of their costs and benefits and, most importantly, *where* they are useful. They can be an expensive intervention, and still, few studies have successfully estimated the causal effect of computer use on learning outcomes for low-income students in different usage environments. This study isolates the relationship between computer use in different environments and problem-solving skills for economically-disadvantaged populations in a sample of high- and low-income countries by comparing the outcomes for students matched on the likelihood of using a computer. It employs more recent data and newer statistical tools to better address deficiencies in previous evaluations.

Research Questions and Hypotheses

I use information from the 2003 Programme for International Student Assessment (PISA) to model the relationship between student computer use in different environments and problem-solving skills for students from economically and socially disadvantaged backgrounds. The overall question I seek to answer is, "How is computer use related to higher scores on an assessment of problem-solving skills for underserved students?" More specifically, I match students using propensity scores for the likelihood of using a computer in a given environment, and I ask:

- Do students who are similarly likely to use a computer have higher problem-solving scores when they use it?
- Do these higher scores differ based on the environment where the student uses the computer?
- Is this problem-solving score difference for underserved students consistent across national contexts and across various computer-based activities?

I test these research questions by creating a matched sample of students equally likely to use computers and then comparing the "treatment" group that reports computer use to the "control" group that does not. I hypothesize that, contrary to technologies past, computers are an effective way of supporting the acquisition of problem-solving skills for diverse populations, including and specifically, traditionally marginalized groups.

However, to be effective, the technology environment must be conducive to thoughtful exploration and access for unique students. Previous studies of computer use have not fully taken into account how important the usage context is to learning; I include both the immediate learning context and national cultural environment of the intervention in analysis. It is vital that policymakers understand with more certainty the complexities of *how* computer-based learning may or may not be effective.

Phenomena and Hypotheses

Based on limited evidence pointing to the possible utility of computer use as well as on the theoretical relationship I describe above and in more detail in the following conceptual framework, I hypothesize that students from low-income backgrounds who use computers will have higher scores on assessments of problem-solving skills than those who do not, holding other factors equal. Further, because of literature on problem-solving and initial findings on the unsupervised use of computers (Inamdar & Kulkarni, 2007; Papert, 1984; DeBoer, 2009), I hypothesize that this effect will be more noticeable for students who use the computers in independent learning environments (in the home or "elsewhere") rather than in the directed environment of the school. Finally, because I hypothesize that the learning and cultural contexts matter (see chapter 1), I hypothesize that there will be noticeable heterogeneity of the treatment effect across a diverse sample of countries.

Conceptual Framework and Literature

The new advancement of computerized learning merits a fresh look, especially with the finances and policy attention it receives. Where previous studies have not fully incorporated the key factor of the student's environment, I situate my work in a sociological perspective. Further, I incorporate constructivism, which notes the importance of the learning context and provides the conceptual foundation for numerous recent digital learning programs (Piaget, 1962). Learning theory overall suggests that computers are educational tools with huge potential; empirical evidence corroborates the relationship between computers and constructivist pedagogy in the classroom (Gulek and Demirtas, 2005; Becker, 2001; Roschelle, 2000). The constructivist framework has even been expanded into the "constructionist" framework, used extensively in work with early LOGO interventions (Papert & Harel, 1991). However, the literature is relatively small given the popular attention it received. In addition, it has focused on access and usage rather than outcomes, and scholars note that access clearly does not always translate to use or utility in learning (Smerdon & Cronen, 2000). More importantly, empirical research on computers has not been married to relevant research on the social context of learning as it is here.

I draw on constructivism and theoretical frameworks of the social context of education to investigate three important areas: first, whether computer use matters at all for the academic outcomes of underprivileged students; second, whether this effectiveness varies based on where the computers are used; and third, whether variation in effectiveness can be explained by national factors or usage behavior. (The conceptual model is given in Figure 1.)

Computer Use Effects on Academic Outcomes: Few Rigorous Studies, Little Consensus (RQ1)

The general question of computers' utility in education has not been answered conclusively (research question 1). Numerous individual studies find small but significant effects of school-based computer interventions for student achievement (e.g., Papanastasiou et al. 2003; Wittwer & Senkbeil, 2007; Chen & Liu, 2007). The conflict between studies that find no effects (e.g., Angrist &Lavy, 2002) and studies that find significant positive effects (e.g., Banerjee et al., 2007) persists. The few quantitatively rigorous randomized control trials are those mentioned in this section. Recent meta-analyses in the United States (Soe et al., 2000) and around the world (DeBoer, 2010a) combine independent study results and confirm small but significant effects. However, these effects display a large amount of heterogeneity that cannot be explained by available information, which provokes the next research question.

Numerous explanations are given for why computer use affects academic outcomes. First, computer-assisted learning (CAL) is seen as a more enjoyable venue for learning, one often associated with play, for which children may have more enthusiasm and therefore a higher uptake of knowledge transferred there (e.g., Mumtaz, 2001). Computers may be more effective because of their capability to individualize instruction (Barrow, Markman, & Rouse, 2008). And, though computer use may not increase math or reading scores, it is shown to increase computer fluency and cognitive skills (Malamud & Pop-Eleches, 2010). This may be due to the fact that computer can may encourage self-directed learning and problem-solving, which I detail in the next section.

Learning Context: Different Environments for Use (RQ2)

Heterogeneity may be largely attributable to the greatly-varying contexts in which the aforementioned studies took place. Many previous studies of school-based computer interventions condition on socioeconomic status (SES) and other factors known to be closely associated with academic achievement (e.g., Tien & Fu, 2008; Du et al. 2004; Prinsen et al., 2007). My study explicitly matches students based on these important background characteristics and investigates the effects of use of computers outside of school as well as in school to understand the individual and interacted effects of different computer use environments.

Research on computer use outside of school is sparse but shows some promise of the effectiveness of independent exploration on the machines. Some prior studies suggest that independent acquisition of computer skills could enhance achievement (Garthwait, 2007; So & Kong, 2007; Inamdar & Kulkarni, 2007; Kam, Ramachandran, Sahni, & Canny, 2006). Other studies (Wittwer & Senkbeil, 2007; Papanastasiou et al., 2003) find that availability of a computer and certain types of use can have little or negative association with increased achievement, though particular activities (e.g., problem-solving) are associated with increased achievement. Empirical tests of a technology intervention (Jasper) that focuses on group learning also finds evidence of the differential processes of learning in different environments (Young & McNeese, 1993).

Two explanations drive hypotheses for this research question. First, independent use of computers is a type of self-directed learning. As students can explore on their own, learn about topics of their own interest, make mistakes, and solve their own challenges, it stands to reason they will come away with a deeper and more persistent knowledge of the topic. Second, as students use computers for both independent exploration and more formal education purposes, the computers enter the space of their learning community. Earlier research by Scardamalia and Bereiter (1994) describe how IT can create a framework for schools as communities of knowledge. Computers can support these communities, and they can also extend learning to be constructed in out-of-school communities. The creation of these knowledge communities differs between the environments in which they are constructed. My three models isolate the effects of computer use "in school", "at home", and "elsewhere" (research question 2). Problem-solving scores will be used in the same models to determine differences in the effects of varying use environments on outcomes as suggested by the literature and conceptual model.

Why the variation? National Policy Differences and Individual Behavior (RQ3)

Beyond estimating the effects of computer use, I push this study further by investigating macro-factors that may cause heterogeneity in the observed effects. First, variation in national policy creates vastly different computer usage environments for students. I hypothesize that there will be differences in the estimated effects by country, and I test this empirically in addition to highlighting the policy environments that could lead to this variation.

Further, previous studies have drawn conclusions about the effectiveness of computer use (e.g., United States Department of Education, 2010) without noting what students were doing on the computers. In PISA 2003, I have access to student reports of what programs they use the most. I note the significant differences in usage behavior between more- and less-frequent computer users and relate this to the effectiveness of computer use.

A Novel Focus on Underprivileged Populations in Diverse Nations

National differences. The issue of access for lower-income students is an immediate threat to unbiased estimates as well as a policy challenge; the digital divide manifests itself between high- and low-income countries (Compare the near-universal availability of computers in Korean households to the less than 40% availability in Thailand. [PISA, 2003]) as well as for populations within countries (Du et al, 2004). In previous research, the digital divide has usually been studied in an oversimplified way—comparing the usage of the "haves" and the "have-nots". Further, scholars demonstrate that, when low-income students use computers in school, they are often doing so in a more rote-learning environment, and they receive differential benefits from its use (Du et al., 2004). As a population that has been overlooked or lumped into previous analyses, students from disadvantaged backgrounds merit a focused study. In my paper, I focus on under-served students. I first describe here the differences in computer learning environments across countries, and I then detail the framework for investigating low-income students' use of computers in particular.

Statistics describing the availability and use of computers in schools reveal stark differences between countries (World Economic Forum, 2008). Country-level factors such as culture, national income level, investment in digital education tools, and other factors are clearly important. While the differences between cultures are part of the very motivation for looking at computer use in different countries, they also necessitate care in conducting the investigation. Some reports call into question the validity of comparing and contrasting vastly different cultures, pedagogies, and school systems and caution heavily against drawing firm conclusions from international assessment data (e.g., Rotberg, 2006). I do not make causal arguments in juxtaposing these national contexts; I recognize the process by which PISA's information was gathered (OECD, 2005) and compare results in order to generate future directions for research and possible policy implications for education leaders.

The five countries included in this study all have unique digital learning environments and are undergoing important changes in recent years. In the United States, computer use grew in the five years preceding the PISA data collection, and the southeast leads computer usage, possibly due to within-country regional competitiveness (Becker, 2001). Students across Canada share computers at approximately five students per computer—better than the OECD average—but use them less frequently (40% frequent use, 4 points below the OECD average [Bussiere, Cartwright, & Knighton, 2004]). At the time of PISA 2003, Thailand was in the process of implementing national-level policies to support technology use in education (Rumpagaporn & Darmawan, 2007). Korea reports that there is at least one computer per school classroom, and over 20% of teachers use them in every class (Ministry of Education, Science, and Technology, 2008). Finally, since the first PISA data included in this study, Uruguay decided to lead the One Laptop Per Child charge and hand out computers to over a quarter million children, over 70% of whom previously had no computer at home (One Laptop Per Child, 2009).

The digital divide. In each of these countries, the gaps between students who do and do not have access to computers, who do and do not use computers, and who do or do not have socioeconomic or cultural privilege are closely related. Not only are there clear systematic differences in technology penetration between groups, but a growing body of more recent research suggests that attempts to add technology to communities only serve to widen extant disparities.

Data from North Carolina show that there are indeed racial and SES differences in home computer access and use (Vigdor & Ladd, 2010). The study offers significant negative estimates of the academic effects of introducing computers and high-speed internet in the homes of students in this panel dataset. Elsewhere (e.g., Wainer et al., 2008), evidence from Brazil shows computer use and access segmented by students' socioeconomic status. The authors further find that educational outcomes are negatively correlated to computer use and positively correlated to access, a differential effect that widens the difference for poorer students.

These (and other) studies point to the importance of where and how technology is used. Researchers and policymakers alike must understand that simply focusing on providing access neglects the recognition that users must have the wherewithal to make sense of digital tools. A study using PISA 2006 (OECD, 2010) characterizes this "second digital divide, noting that some households have the right competencies to maximize the benefits of the technology. Results from previous work imply a need for targeted interventions for low-SES students, yet few studies focus solely on underprivileged student use. I sample from within a larger dataset to isolate the effects of computer use solely for underserved students, matching similar students with one another in order to advance policymakers' understanding of technology use as a cultural capital question.

Cultural capital. Bourdieu's theory of cultural capital (Bourdieu, 1977) describes the ways that social class markers, norms, and values interact in the educational system to further the privilege of more powerful social groups. Though not included in Bourdieu's original scheme, and not yet widely researched, digital technologies are a part of this framework as well, and "technological capital" is an important contemporary component of social and cultural capital. Groups with lower socio-cultural and economic status are often those with lower access and use of digital technologies. The persistence of the "digital divide" moves beyond just the access that communities have; they employ different sources of cultural capital, and the role of informational technology in individuals' lives is socially constructed (Rojas et al., 2012).

Warschauer and Matuchniak (2010) argue that it is not just access that is important for educational technology, but creating a supportive environment. Their argument that a fertile environment for IT to be useful introduces the idea of IT as a context-dependent tool. Emmison and Frow (1998) discuss the applicability of cultural capital to issues of IT, including descriptions of the correlation between "traditional" measures of cultural capital (e.g., museum visits) with household computer ownership. In most previous research, the "digital divide" and characterizations of access and use in underserved populations are seen through a (power) framework of "Western ideologies of technology use"; however, focusing on particular subgroups allows the researcher to recognize and value the types of use of members of a non-dominant group (Brock, Kvasny, & Hales, 2010). I build on these limited empirical and theoretical pieces to provide an explicit focus on the importance of technical capital in understanding social and human capital development.

Methodological Framework

Methodologically, I draw heavily on Rubin's work identifying a statistical solution to the problem of causal inference (Rubin, 1974), estimating treatment effects using propensity score matching (Rubin, 2001), and using multiple imputation (Little & Rubin, 2003).

As there are few rigorous studies that investigate computer use and achievement, so there are also few that use propensity score matching. It has been used to match students and compare computerized to paper-based testing (Puhan, Boughton, & Kim, 2007). Xin and Zou (2010) use similar methods to move towards answering the causal question of the effect of frequent computer use on math scores. Spiezia (2010) conducts a similar study using PISA 2006 and estimates a selection function for the frequency of student computer use. I address problems created by this method by employing a generalized propensity score procedure, building off of theoretical work on propensity score matching by Rosenbaum and Rubin (1983), Imbens's extension to multi-valued treatments (2000), and numerous examples from the medical literature of empirical work using the same procedure (e.g., Foster, 2003; Feng et al., 2010). For example, Foster (2003) investigates children's response to mental health services by using the inverse of the propensity for a certain dose as a weight to adjust estimates, similar to the methods I detail below for my study.

Methods

Data

The sample for my project comes from PISA 2003 which included, for the first time, a set of questions concerning information and communication technology (ICT) as well as an assessment section on problem-solving skills. Also, the PISA assessment rotates its focus section each year. (The 2003 focus was on mathematics.) The 2003 PISA student questionnaire (OECD 2003a) and Information Communication Technology (ICT) familiarity questionnaire (OECD 2003b) both address issues of student usage behaviors in terms of time, location, and ease of use. Data is available on students from over forty different countries. I can compare the effectiveness of computers in promoting academic achievement for underserved populations in the US to disadvantaged populations in other high-income, diverse countries as well as more homogenous or lower-income countries. I limit my sample to a selection of countries to be compared and contrasted to the US case: another high-income, diverse country (Canada); a high-income, more homogenous country often cited as having an effective education system (Korea); a low-income, Latin American country (Uruguay), and a low-income, South-east Asian country (Thailand). I further limit my sample by focusing on the bottom quarter of families based on the economic and socio-cultural status index relative for each country.

PISA offers fertile ground for redressing the dearth in the literature on computer use and achievement and is in fact used by two studies previously mentioned as all or part of their measurement tools. With the inclusion of questions specifically investigating students' use of computers in different settings, researchers can look at the relationship of newer technology to an established assessment of learning outcomes. Also, the other PISA assessments gather information about students' use of computers (though questions are not identical to PISA 2003). The possibility therefore exists for further work taking advantage of PISA's longitudinal country-level information; I use PISA 2009 to nearly replicate this study.

Sampling Frame

The sampling design for this assessment is a two stage, stratified random sample, with the first level being the schools and the second being the students within the schools. Countries were allowed to pursue national options where they did not interfere with the general test collection. In some cases, the primary sampling unit was an area (such as a province) if lists of schools were not available at the national level.

Fifteen-year-olds in grades 5 and higher in official educational programs were chosen as the proxy for students at the end of compulsory education. These students, therefore, are measured on what is deemed to be the knowledge and skills essential for full participation in society. Approximately 4,500 students were targeted in each participating country—35 students were chosen in 150 schools (to address response rates). Schools were sampled with a probability proportional to their size (the estimated number of 15 year olds at the school). The students are a nationally representative sample of students in participating countries. The final sample size is 49,924 (Canada: 27,953; Korea: 5444; Thailand: 5236; United States: 5456; and Uruguay: 5835). When limited to the bottom quarter of ESCS, the final working dataset contains 12,116 observations, approximately 6,500 for Canada and approximately 1,300 for the other four countries.

Survey and Assessment

Participants in the PISA assessments include all of the OECD members—wealthy developed nations concentrated in Western Europe—as well as OECD partners who have chosen to participate in the current assessment. The countries participating in PISA 2003 are given in Table 1. The ICT survey was given as an international option for countries participating in PISA 2003. Thirty-two of the forty-one countries in PISA 2003 chose to distribute the ICT questionnaire to students in their studies. (See Table 1 for countries.)

Limitations

Limitations to this work include the complexity of the three use environments, the generalizability of the PISA sample, and the time order requirement to firmly establish causality. The former makes interpretation of coefficients challenging, but this richer picture of computer use is one of the unique contributions of my work. The latter limitations are weaknesses in the study that are found in other PISA work and all previous non-RCT studies. While useful steps are taken to address endogeneity concerns in my work, it may still be a problem; the cross-sectional data will never be as airtight as a randomized trial. There are nevertheless great benefits to increasing understanding of the relationships between computer use and academic outcomes, and this study provides useful baseline data for potential RCTs. Future work may incorporate information from the mathematics sub-scales, the Trends in International Math and Science Study (TIMSS), or other datasets to incorporate more detailed outcome or curricular information or to look at trends over time.

Variables

Treatment variables and computer controls are drawn from the ICT questionnaire. There are questions on the ICT questionnaire that address availability and use of computers at school, at home, and "elsewhere". Other controls are drawn from the student questionnaire, and my outcome variables are all drawn from the PISA assessment instrument. Independent variables of interest are detailed in the "variable list" document. Total student weights, a set of frequency weights for the assessment, are used to address the complex survey design of PISA, which samples schools and then 15 year olds within schools and allows countries to stratify and oversample with some flexibility. The outcome variable of interest is the problem-solving skills score. Outcome variables for each country (problem-solving literacy), when adjusted for survey design, all have means between 480 and 490 with standard deviations around 100.

Modeling Strategy

Causal Inference

In order to estimate the causal effect of computer use for low-SES students, I am faced with two problems—the classic counterfactual problem and the problem of selection bias. First, I am interested in problem-solving achievement (outcome value Y) for an individual (i) when that individual uses a computer (treatment *t*) versus when that individual does not use a computer (control *c*). I write this as below, following Rubin (1974, as cited in Holland, 1986):

effect of t = $Y_t(i) - Y_c(i)$

However, because it is impossible to observe two different treatment conditions on the same individual, I must observe an average effect (T) over a population of i's:

$E(Y_t - Y_c) = T$, or, by extension $E(Y_t) - E(Y_c) = T$.

The latter implies that averaging over multiple distinct individuals can provide information about the average treatment effect for a population. However, this is only valid where the assignment to treatment is unrelated to factors that would influence the outcome measure, that using a computer is unrelated to factors such as parental education or attitudes towards learning that might also influence problem solving achievement. Herein lies the second problem in estimating the causal effect of computer use for low income students.

In addition to the problem of observing both treatment and control situations on the same individual, I am faced with a nonrandomized treatment in a cross-sectional dataset. Individuals assigned to control and treatment groups may differ on observable and unobservable traits that are also linked to different outcomes; students who use a computer may also be ones who have greater resources at home, which has an established link to academic outcomes. This may bias the measure of the average treatment effect. In order to recover unbiased estimates of the relationship between computer use and academic outcomes, I create a matched sample of students who are similarly likely to use computers. While I must match on observable factors, I assume that these factors are also related to unobservable factors that threaten the unbiased estimate of the treatment effect, and I can come closer to causation.

In this dataset, there are a number of factors used to predict computer use—student factors such as age and gender, family background factors such as parental education and family structure, and home factors such as possession of a computer. I cannot simply match on covariates—I am limited by the dimensionality of covariate matching because of my sample size. One of the newer tools in the policy analyst's toolbox today is propensity score matching. Rubin (2001) describes, for an observational study like mine, estimating a probability e_i that a unit i will receive a treatment ($W_t = 1$) versus not receive a treatment ($W_t = 0$) given a vector of certain observed outcomes $\mathbf{X}_i$. This assumes that the treatment assignment is independent of confounding covariates given a certain propensity score (Conditional Independence Assumption).

Still, I can only control for observable factors, a major caveat in observational propensity score matching versus a randomized trial. Rubin also notes that the possibility of differences due to unobservables even after matching on important observables may be addressed by testing different models for sensitivity analysis and testing structural assumptions, which I do by running additional regressions using control variables on the matched sample and employing a multi-level prediction model that takes into account the nested structure of students within schools within countries.

While this is a cross-sectional dataset, it still needs to be clear that the variables used to match treatment and control observations are not affected by participation. This is a difficult relationship to distinguish, as the argument could be made that a variable like “confidence on routine [computer-based] tasks” is an outcome of prior computer use. However, the PISA questionnaire explicitly asks about current use, and a characteristic such as computer confidence is more fixed over time prior to reporting current use levels.

Results

Missing data

While missing data do not plague the final working dataset, there are a number of key variables that are missing information. There are noticeable amounts of missing data particularly in some of the computer availability and specific use variables. However, there does not appear to be a systematic pattern to this missing data. All of the variables have over 75% of their information; the most missing data is 22.13% for the question “Where did you learn computers?” Further, out of the 12,116 observation dataset, less than 10% of the observations are missing on more than five variables, and these are often the “type of use” questions.

Nevertheless, I impute missing data to address potential bias from casewise deletion of a sample of the dataset that is not Missing Completely at Random (MCAR) as well as to increase the efficiency of my estimates. I estimate five imputed datasets. (Rubin [1987] shows that even with a rate of missing information of 0.5, five imputations will yield estimates over 90% efficient.) Missing data are imputed separately for each country using all of the covariates in the fully-specified PSM prediction model and the ATT model, taking into account the complex sampling design. A comparison of results prior to imputing missing data and after is given in the Appendix. The illustration there suggests that missing data biases results downwards and slightly increases the variance of point estimates; including imputed data shows larger, significant positive effects. A set of five imputed datasets is estimated for each of the five outcomes (plausible values). More detail on plausible values is given in the following section.

Plausible Values

The PISA cognitive assessment is administered in a bib spiral manner. Fourteen forms of the cognitive item assessment are administered with some overlap, and item response theory (IRT) is used to predict a student's overall score from the items to which a student actually responded. PISA computes a posterior distribution around the values given for students and provides five random values drawn from these distributions for each student.

$$score_i = E[\textit{posterior distribution of full score for student } i]$$

While many studies only conduct analyses on one of the plausible values, and depending on only one plausible value for analysis should not bias coefficient estimates, this underestimates the variance of the final coefficient estimates.

$$\hat{\beta}_{ATT} = \text{ave(coefficient estimates for each iteration)} = (\hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3 + \hat{\beta}_4 + \hat{\beta}_5) / 5$$

The procedure for final coefficient and variance estimates is similar to the creation and estimation of coefficients based on imputed data. To estimate coefficient variance, both the variation within each "sample" and between the five "samples" must be incorporated.

$$\text{average of the variance within each ``sample''} = \sigma^2_{\hat{\beta}} = (\sigma^2_{\hat{\beta}_1} + \sigma^2_{\hat{\beta}_2} + \sigma^2_{\hat{\beta}_3} + \sigma^2_{\hat{\beta}_4} + \sigma^2_{\hat{\beta}_5})/5$$

The variance of this error across the full sample of plausible values is given using the estimator for unbiased sample variance:

variance of the measurement error = $\sigma^2_{\sigma^2} = (\frac{1}{M-1})*\sum_{i=1}^{M}(\hat{\beta}\mathrm{i} - \hat{\beta})^2$

Finally, combining the two variances gives:

$\sigma^2_{total} = (\sigma^2_{\hat{\beta}_1} + \sigma^2_{\hat{\beta}_2} + \sigma^2_{\hat{\beta}_3} + \sigma^2_{\hat{\beta}_4} + \sigma^2_{\hat{\beta}_5})/5 + (1+1/M)(\frac{1}{M-1})*\sum_{i=1}^{M}(\hat{\beta}\mathrm{i} - \hat{\beta})^2$

Any differences between standard error estimates between coefficients from different plausible values will increase the total variance estimates, decreasing the efficiency of the estimated treatment effect; comparisons are given in Appendix C. PISA (2011) gives more detail on this procedure for estimating regression coefficients and other procedures using plausible values. In reporting my results, variance estimates for coefficients of interest are given including both within- and between-estimate variation. I also take into account PISA's complex sampling design. Accounting for the complex sampling procedure in PISA while predicting the propensity for computer use does not change the estimated effects at the 1/100th place.

Matching

Choosing covariates for prediction. An important consideration is the possible association of computer usage with other variables that are known to be closely associated with academic achievement, for example, socioeconomic status (Tien & Fu, 2008; Du et al. 2004), gender (Prinsen et al., 2007), or geography (DeBoer, 2009). I use vectors of student individual and home background characteristics, school resource variables, and national identifiers to create matched comparison groups (see variable list).

To specify the prediction model, I use what Lee (2006) calls the “DW” test, after Dehejia and Wahba (1999). The authors iteratively estimate the propensity score, check for balance on covariates, and reformulate the propensity score. Established connections have been made between computer use and student characteristics (e.g., gender [Du et al., 2004]), family background (e.g., parental education), and self-efficacy (e.g., confidence on computerized tasks); these factors have also been shown to predict academic achievement

PISA’s rich dataset has a number of factors recorded for students, their families, and their attitudes towards learning tools. After conducting this specification test for an ordinal logistic regression, I use the following set of covariates to predict treatment status

p(status = t | X) = f(student chars, family chars, confidence)

where *student chars: age, grade (compared to modal grade in country), gender*

family chars: possess computer, highest parental occupation status, parental education, home possessions index, non-nuclear family structure

and *confidence chars: indices of confidence on routine computerized tasks, internet tasks, high-level tasks, and mathematics self-efficacy*

Table 2 shows the significance of predictors in the ordinal logistic regression (again, an example without missing data, for use at school from the USA) predicting treatment level.

Choosing a matching algorithm. While there are a number of matching estimators used in binary PSM, I am faced with different challenges since the treatment is reported at ordinal levels in this study. Instead of using a binary PS, I use a “generalized propensity score”. This score can be incorporated into analysis either as a weight or as a regressor in a prediction model for achievement. As guiding examples, I look at Dearing, McCartney, & Taylor (2009), who use weights, and Hirano and Imbens (2004), who employ regression.

Estimating the Propensity Score

After imputing relevant independent variables for each treatment within each country, I proceed with the PSM procedure. I have already defined a prediction model; the subsequent steps are to estimate the expected outcome adjusting for the generalized propensity score and to average over the entire dose-response function, following Hirano and Imbens (2004). I use PISA's provided balanced repeated replicates for final effect estimates. I focus on their method (regression method, rather than a second set of weights) for results reporting.

Treatment-dose response model. While propensity score models normally estimate the effect of a binary treatment, computer use in PISA is not measured as a binary variable. Students respond with a choice between five levels of how frequent their use is of computers, ranging from "almost every day" to "never".

Imbens (2000) extends Rosenbaum and Rubin's (1983) propensity score methodology to treatments with multiple levels. By maintaining the assumption of weak unconfoundedness, and requiring only the independence of each potential outcome at a particular treatment level, the average outcome can be estimated by conditioning on the generalized propensity score, a score that gives the conditional probability of receiving a particular *level* of treatment, rather than just receiving the treatment, given pre-treatment variables. Imbens demonstrates that ordered levels of treatment (as is the case in this study) can be estimated using an ordinal logistic regression. He then describes estimation of the treatment effect by averaging the conditional expectation of the outcome given treatment levels and propensity scores as well as using the propensity scores as weights. I test both methods. However, the weighting method does not also allow for survey weights to be taken into account, so I concentrate my final report on results using the regression method.

I use an ordered probit model to predict the level of usage a student will report in each environment. After estimation, I generate predicted values for each level of use; I do not assume that the change between each treatment is incremental, so with this method, I have a generalized propensity score for each level of use. Results reported (e.g., Table 4) give the estimated treatment effect coefficient for each treatment level in regressions that include levels of use as dummy variables as well as each general propensity score as a vector of regressors or as probability weights.

Balance

Not only am I concerned about balancing treated and untreated observations in general, I am concerned about the difference in how the samples may be look in different countries. As can be seen from Figure 2, the spread of reported computer usage in different contexts is very different in the five sample countries, in particular, in terms of home use. This is the full sample, however, and the data also need to pass a balancing test in the matched sample.

A variety of balancing tests exists to ascertain whether observations in treatment/control groups matched on propensity scores have similar distributions of observable covariates. Since the propensity scores serve the purpose of balancing the distribution of observed covariates between control and treatment groups, they are judged on this balance rather than on model fit (Lee, 2006). Following Lee (2006), I conduct both a "specification" balancing test and an "after matching" balancing test. In the case of the generalized propensity score, these procedures are similar; Hirano and Imbens (2004) describe testing the differences in means of the covariates between treated and untreated observations in each treatment category.

After balancing, I test for equality of each covariate mean between groups. Table 2 shows an example of the balance of predictive covariates before and after matching (for the USA, use in school, before imputing missing data). Covariates that differ significantly across the treatment levels do not vary significantly when adjusted by the generalized propensity score.

As noted above, the actual numbers for treated cases at especially the highest treatment levels becomes small. For example, in the case of "use at home" in Thailand, there are only 16 treated cases in the highest treatment level. Zhao (2004) finds that PSM is not better than covariate matching for small samples; however, in my case, a small sample size limits the applicability of covariate matching because of its dimensional needs. Blackford (2009) demonstrates a medical application of propensity score matching to a sample with 77 "treated" cases in the analytic sample. She notes that a logistic prediction model requires 10 observations per confounder, a condition which is satisfied in my study even for the most extreme treatment situations.

In the discussion of the results that follows, I report treatment effects that are significant and the context in which they are significant—in which environment the computer is used, in which country, and at what level of use. Results tables also describe the estimated treatment effects by these three dimensions.

Research Question 1: Does computer use affect problem-solving achievement for low-income students?

Table 1 gives results for computer use overall and for different treatment dosage levels. I only report the estimates for treatment effects, though the regression model also includes the propensity scores as covariates, and the weighting model includes important predictors of the outcome as well as incorporating the propensity score as a weight. Overall use (operationalized as the highest use in any location) has a statistically and practically significant effect on problem solving skills over not using computers at all in the United States and Canada. Results in other countries are not statistically significant. Effect sizes go as high as .68 standard deviations for occasional computer use in the United States. It should be noted, however, that these effects are insignificant in the model that uses propensity scores as weights. Effects are insignificant in other countries. As in the previously-noted literature, the utility of computers is a question with mixed results; the following two research questions shed more light on which contexts may actually be useful places to use computers.

Research Question 2: Does the effect of computer use vary by where it takes place?

Table 1 also gives results for computer use by context. The effectiveness of computer use appears highly context dependent. Use of computers at school varies by country. It has a significant, positive effect on problem-solving skills in the United States and Canada. Use of computers in schools does not have a significant effect for low-income students in Thailand. However, at high levels, computer use in schools has a significant negative effect on problem-solving skills in Uruguay and Korea.

Across these diverse national contexts and different dosage levels, using a computer at home does not have a positive effect on problem-solving skills. In a few cases, using a computer at home is related to lower problem-solving skills.

Using a computer "elsewhere" (somewhere besides school or the student's home) varies by the level of use. This student-driven use is significantly related to lower problem-solving scores for the most high-frequency levels of use. But, at lower levels, using a computer outside of the more "traditional" contexts of school or home is related to higher levels of problem-solving achievement.

Research Question 3: Does the effect depend on the type of use? What differences in the national context can explain variation in the estimated effects?

I investigate the significant differences in usage type reported by students at different dosage levels. I combine the information on significant treatment effects at different dosages for each country with the rankings of usage for different programs. For example, I look at the most frequently-used programs for Canadian students who report "daily", "weekly", "monthly", "rarely", and "never" using computers at school, and I note how this might relate to the significance of estimated effects. ANOVA tests of differences in mean program use by amount of overall computer usage are significant in the cases mentioned, but I detail further which programs are used more frequently. What are students using the computers for that might explain differences in the effect of computers on achievement? What national policies might help explain differences?

In the United States, computer use overall seems beneficial. At every level of treatment, students have higher problem-solving scores than those who never use computers. The reported student usage of programs has students “using the internet for information” the most frequently, except for students who report that they never use the computer. On the contrary, students who “never” use the computer at school report using computers to download the most. For students who use the computer at home, the only significant result is that using it on a weekly basis has a negative effect; those students are on computers to use the internet for information. However, at school, using the internet for information is reported at a high level for students for whom computer use is beneficial. Perhaps guided use of the information available on the internet is related to the utility of computers. For independent computer use, the students who are using computers independently and not benefitting from them are using them to access computer games, where students who use them infrequently and see a positive effect from their use are using computers more for learning programs and for getting information on the internet and using internet software.

Canadian results are similar. School use, which is overall positive for students, shows more infrequent users use the internet for information less and for downloading music more. They use computers more frequently for chatting, while more frequent users use the computer for games more. Home use, which is not beneficial, also sees students using the computers for chatting, though this is less for lower levels of use. The students who use computers “elsewhere” frequently and see negative effects from them use the computers more for downloading software and less for getting information or using a word processing program.

In Korea, frequent school use actually has a negative effect. Frequent users are using the computers more for programming and graphing and less for learning school material. Students using the computers “elsewhere” at high levels see negative effects; those students are using the computers less for learning school material. On the other hand, less frequent “elsewhere” users are using the computers more for chatting and graphing, drawing, or painting, and benefitting from it.

In Uruguay, frequent school use has a negative effect. Students using computers at that level use them less for getting information from the internet or chatting. Home use is also not beneficial—students use the computers more for computer games, though, interestingly, they also use them more for learning school material and using educational software. In Thailand, usage patterns for the computers did not display easily notable patterns related to the measured effects.

In countries where school use is good, students use the computers to access the internet and gather information. In the home, though, students use the internet for getting information, chatting, playing, and learning; but, in that context, computer use is not beneficial. Most notable is that the frequent “elsewhere” users are using computers more for what might be characterized as less complex tasks—downloading information or playing games. On the other hand, students who use the computers “elsewhere”, but do so to a lesser extent, are benefitting academically for this use. These students use the computers more for chatting, drawing, and getting information from the internet. Future studies could focus on a particular program use on computers to follow up on the measurement of the overall effects of computer use given here.

Checks of Consistency of Estimates

As I have to make a number of research design choices, I test a number of specifications to determine how consistent my estimates of the treatment effect are. I test multiple models for determining the propensity score and for using the generalized propensity score in estimating treatment effects. Further, I apply the same model to the four countries that also participate in the ICT questionnaire in PISA 2009. I use math scores here as my outcome of interest, as problem-solving skills were not assessed. Besides this difference, my approach is comparable to a repeated cross-section design, replicating the same study across multiple years.

PISA 2009. Compared to results in Tables 2 and 3, the results in PISA 2009 show Canada, Korea, and Uruguay estimates for "any use" and "home use" continuing to be positive and significant effects on mathematics achievement. Similarly, the effectiveness of school use appears to be mixed. Estimates are insignificant or negative in all countries except for Thailand, where school use is strongly positive. This is consistent with the overall findings from 2003 on problem solving, though the fine grain on the treatment dosage available in the 2003 questionnaire is no longer present.

Multi-level prediction model. I recognize that students in this assessment are nested within both schools and countries. Taking into account the multi-level nature of the data would more accurately reflect the true structure of the treatment—students who may or may not use computers in different environments are affected by the choices, behaviors, and backgrounds of the students who surround them in these different environments. As such, the correct model to generate the predicted values for the generalized propensity score would be a random effects model, and I use this approach.

Arpino and Mealli (2011), as an example reference study, demonstrate that a general random effects model that accounts for the hierarchical structure of data performs better than more parsimonious models. However, I find the results consistent (at the hundredths' place) across these prediction models.

Discussion and Policy Implications

As policymakers struggle to determine where computers are an effective use of time and money for increasing low-income students' problem-solving skills, more attention needs to be paid to the context in which computers are used and what they are used for. Further, an understanding of how computers' utility in different contexts relates to constructivism and learning theory more broadly would support targeting learning interventions effectively to students.

School use appears to be beneficial in the two large, diverse, high income countries in this study. Policymakers should better understand what about the opportunities to use computers at school is relevant for problem-solving and how school use could be taken advantage of even more. In the other three countries, school use policies need revision. While schools are often the places where computers are most available to students in these contexts, the saturation of access does not necessarily lead to higher learning outcomes. In fact, in the lower-income countries—Uruguay and Thailand—school use is related to lower problem-solving skills. In both of these contexts, computer-based learning interventions have increased in schools, but the necessary support for teacher training on the machines may not have had the chance to catch up to the computers' availability. While major pushes for access characterize computer placement in schools, the focus on access may actually be detrimental to the learning process. Access without thought for how the computers are being used may actually take away from more valuable learning time on other tasks.

Across all of the countries in the study, more care should be taken in student use of computers in the home, as use in this context is not significantly helpful and, in fact, is often related to lower problem-solving scores. Interventions with parents or take-home work conscientiously linked to problem-solving could support computer use in this context in ways more relevant to academic learning.

However, when students take the responsibility upon themselves of using computers to a moderate extent in an environment outside of the home or school, they benefit. Use "elsewhere" has the most potential for development as an intervention. A moderate amount of use could relate to higher problem-solving skills for students in a variety of countries. Policymakers could encourage and provide for opportunities for using computers on students' own time, allowing them to take the responsibility to use the machines on their own in a self-directed fashion. Computer use has the potential to serve the most under-served students in a host of countries, but only if students are given meaningful tasks and opportunities to learn.

Little Available Rigorous Guidance

This study is motivated by two troubling characteristics of the public and academic understanding of the relationship between computer use and learning—first, that there has been widespread faith in the intervention despite little rigorous evidence for computers’ utility and second, that computers do exhibit the potential for important support of learning for under-served students.

Computer use in education is a high-profile but controversial intervention, with few rigorous, outcomes-based evaluations, disputed results, and claims regarding both high and low effectiveness that may lack thoughtful evidence. In particular, computers have been offered as a unique learning tool for underserved populations, a learning tool that could address the additional challenges prevalent for these students. Low-income students have differential access to technology, but few studies isolate this important population in analysis. Numerous national policy agendas, however, note that focusing on ameliorating the achievement gap is an important national goal (e.g., McKinsey, 2009) and that digital tools should help.

Manipulable, High Priority Intervention

Computer use is a policy variable that is often manipulated but little understood. Despite the lack of consensus on computers' usefulness or best practices for implementation, they have become a prevalent policy tool in many education systems. Policymakers can control availability and access to school computer labs, implement computers in classrooms, encourage personalized education programs (Chen & Liu, 2007), provide off-campus spaces for learning (e.g., Gates Foundation project in Vietnam [Gates Foundation, 2009]), and provide take-home technology (e.g., 1-to-1 computing in Maine, USA [Maine Learning Technology Initiative, 2011]).

In this study I address both the lack of consensus in rigorous evaluations of computer use and the potential that computers have for learning benefits. Local and national policymakers should be interested in conclusive evidence on both structured and unstructured computer use. Computers are becoming as ingrained in quotidian life as televisions are already. Whether they will be washed out with the next wave of technological advancements or continue to advance the quality of learning for students around the world will depend on our understanding of their capacity to provide learning.

Where the theory of constructivism (Piaget, 1962) guided the investigation of the contexts of computer use and educational achievement, so it can also help to understand the results observed. People learn by building on what is familiar with what is interesting. Constructivism describes the process of students scaffolding their learning with new, challenging concepts. In the framework of constructivism, prior knowledge is used to understand new information; through “accommodation and assimilation”, students piece together new knowledge (Piaget, 1962, p.275).

Constructivism underscores the utility of tailoring instruction to the needs of the student, engaging the student in novel activities, and encouraging higher-order thinking skills. While the basic framework of constructivism motivates catering to each student, it also introduces an important tension between the unique needs of an individual and the environment around the learner. On the one hand, the individual builds on his or her own paradigm to gain knowledge; on the other, the learning must happen in context. While von Glasersfeld (1989) argues that the responsibility for learning lies with the learner, Duffy and Jonassen (1992) underscore the importance of collaboration between learners.

This study finds that computer use can be beneficial for the learner when the structured environment of learning both challenges and directs the student’s knowledge acquisition. If students are not being challenged (using computers in environments that without technological support or using computers simply for downloading), their knowledge and skills will not be increased, and, instead, they may take time away from other learning activities. If, however, they can access new information that may be useful to learning, computer use in this environment is beneficial.

Technological Capital

Few researchers and even fewer policymakers have recognized that we must move from the understanding of digital interventions as simplistic learning tools to a conceptualization of technology as a key component of cultural capital. Though computer-assisted learning utilizes a more advanced intervention than its technological predecessors (the television or other electronic learning interventions), it is still a tool that can be used or misused.

The computer and information technology are supposed to have democratizing properties; arguments are widely made for the potential of internet access in the lowest income areas to provide popular empowerment. What is clear from previous work and even in this study, which focuses on low-income populations, is that negative effects are present alongside positive effects. It is not enough to look to technology on its own to solve traditional issues of inequity in educational opportunity. Technology is the same as other tools that may be co-opted and used to reinforce stratification. Unless their particular use is understood, they do not have the desired effect.

Certainly, in some cases, the cultivation of technological capital may actually override traditional boundaries of other markers of socio-cultural status (Kapitzke, 2000). Technological literacy, as a new dimension of both human and cultural capital, has the potential to bypass other entrenched barriers to individual and social development. However, policymakers need to understand how computers are used in various contexts in order for technology to alleviate rather than exacerbate extant gaps.

Technology is a language. And just as linguistic cultural capital translates into building intra-community bonds or bridges to broader social mobility, so technological capital can either reinforce the connections between members of the same group or provide an individual access to communities outside the realm of her birth. Individuals begin to learn the language of technology in their homes, with their peers, and inside their classrooms. The way they interact with technology is heavily context dependent. What kind of technology does a particular community perceive as valuable?

My work finds evidence for a recommendation that self-directed computer use may be useful, but that it benefits from some supervision and/or direction from parents, teachers, or other mentors. Previous studies (e.g., Vigdor & Ladd, 2010; Malamud & Pop-Eleches, 2010) find results that corroborate this recommendation. While children may explore technological tools on their own, the involvement and examples of parents and community members contribute in meaningful ways to the utility of computer use for actual learning.

Even more than other forms of cultural capital, technological literacy is a prescient issue and a misunderstood one. The mixed effects I find here are important; they illustrate the relevance of the usage environment to computers' utility and the ways in which technological capital may have both convergent and divergent effects depending on the environments, levels, and types of use. It is not just that computers are a tool that can be used or misused, it is a question of what is being delivered on them. The ways in which the different offerings of computers in a learning environment can impact achievement are illustrated in this study. In looking at the further training of certified problem solvers who access particular realms of technological capital (i.e., engineers), I continue to develop the concept of technological capital in subsequent chapters.

Figures and Tables

Table 1. *Countries participating in PISA 2003*

Countries			
Australia	Austria	Belgium	***Brazil***
Canada	Czech Republic	Denmark	Finland
France	Germany	Greece	***Hong Kong (China)***
Hungary	Iceland	***Indonesia***	Ireland
Italy	Japan	Korea	**Latvia**
Liechtenstein	*Luxembourg*	***Macao (China)***	Mexico
The Netherlands	New Zealand	*Norway*	Poland
Portugal	**Russian Federation**	**Serbia and Montenegro**	Slovak Republic
Spain	Sweden	Switzerland	**Thailand**
Tunisia	Turkey	United Kingdom	United States
Uruguay			

Note: Countries in bold are non-OECD members; countries in italics did not participate in the ICT survey option.

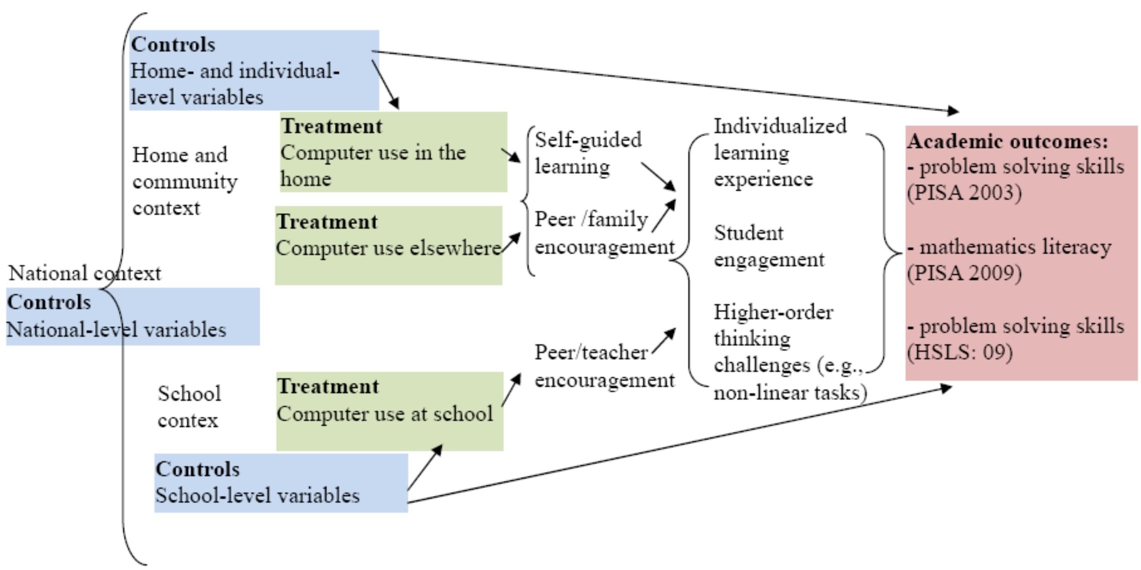

Figure 1. Conceptual model

Table 2. *Significance of differences in means of predictive covariates by treatment level before and after weighting with the generalized propensity score*

Covariate	Significance of F-stat for ANOVA	Significance of F-stat for ANOVA w/GPS
Age	.38	.70
Grade	.62	.65
Gender	.31	.27
Possess computer	.03	.81
Highest parental occupation	.06	.55
Parental education	.85	.98
Home possession	.88	.72
Single parent family	.38	.70
"Other" family structure	.12	.91
Mixed family	.47	.67
Confidence on routine tasks	.14	.13
Confidence with internet	.66	.63
Confidence with high-level tasks	.00	.52
Math self-efficacy	.19	.49

Table 3. *Ordinal logistic regression of covariates for use of computers at school*

Covariate	Coefficient	Standard error
Age	-.15	.11
Grade	.04	.05
Gender	.03	.06
Possess computer	.27	.08
Highest parental occupation	.01	.00
Parental education	.01	.01
Home possession	-.03	.05
Single parent family	-.01	.07
"Other" family structure	.38	.12
Mixed family	-.12	.10
Confidence on routine tasks	.01	.04
Confidence with internet	.07	.05
Confidence with high-level tasks	-.23	.04
Math self-efficacy	-.02	.03

Table 4. *Effectiveness of different levels of computer use over "never" use, regression method*

Treatment level	USA	Korea	Uruguay	Thailand	Canada
Highest computer use anywhere					
Daily	66.98	-18.62	-26.82	-29.92	32.90
	(23.05)	(24.94)	(10.02)	(9.88)	(19.38)
Weekly	46.12	-5.54	0.83	-12.45	32.99
	(23.88)	(25.22)	(9.03)	(9.26)	(19.98)
Monthly	79.59	5.06	26.51	-9.91	36.94
	(23.62)	(24.60)	(13.19)	(9.51)	(20.55)
Rarely	87.05	-50.71	-1.00	-2.70	54.76
	(23.25)	(33.68)	(13.03)	(9.45)	(22.91)
Use at school					
Daily	22.77	-15.20	-36.62	-37.46	-8.11
	(6.00)	(8.67)	(8.58)	(11.32)	(5.60)
Weekly	3.47	-31.70	-19.70	-18.06	-6.89
	(5.65)	(4.18)	(6.91)	(7.55)	(4.45)
Monthly	37.79	-10.83	-12.49	-17.92	4.65
	(6.17)	(5.98)	(9.24)	(8.08)	(5.46)
Rarely	21.95	1.48	-5.14	-6.71	13.52
	(8.01)	(6.69)	(7.11)	(6.40)	(5.31)
Use at home					
Daily	-10.76	-16.69	-5.70	-9.22	20.99
	(9.62)	(6.80)	(16.81)	(16.31)	(10.18)
Weekly	-34.51	-5.78	-22.69	20.87	12.26
	(11.38)	(6.68)	(16.01)	(16.15)	(10.82)
Monthly	-18.90	2.71	39.82	-18.66	7.84
	(10.61)	(7.35)	(32.77)	(19.43)	(11.76)
Rarely	-16.23	-25.06	-37.61	-48.40	-7.45
	(10.71)	(16.59)	(19.95)	(17.54)	(14.94)
Use "elsewhere"					
Daily	-19.64	-41.80	-30.25	5.55	-43.17
	(11.40)	(10.87)	(11.17)	(19.09)	(5.86)
Weekly	-8.96	-21.83	19.60	3.53	-23.42
	(5.55)	(6.39)	(8.54)	(10.11)	(6.19)
Monthly	10.71	6.09	43.38	13.40	-7.97
	(6.72)	(6.64)	(7.77)	(10.41)	(6.04)
Rarely	19.55	12.41	26.48	9.67	-3.21
	(5.38)	(7.88)	(10.70)	(6.17)	(6.36)

Table 5. *Effectiveness of different levels of computer use over "never" use, weighting method*

Treatment level	USA	Korea	Uruguay	Thailand	Canada
Highest computer use anywhere					
Daily	62.34	-23.13	-26.62	-30.03	2.76
	(25.41)	(21.84)	(14.88)	(18.20)	(12.58)
Weekly	43.41	-18.90	-11.46	-18.70	0.51
	(26.44)	(21.50)	(11.37)	(13.01)	(12.90)
Monthly	62.63	3.71	2.07	-16.04	2.46
	(26.68)	(23.07)	(13.91)	(13.22)	(13.67)
Rarely	60.36	-5.64	-21.28	-11.87	-13.66
	(27.18)	(32.93)	(13.60)	(14.07)	(16.85)
Use at school					
Daily	22.20	-16.66	-39.42	-29.26	3.93
	(8.85)	(12.18)	(10.86)	(17.04)	(4.89)
Weekly	7.05	-31.15	-21.35	-17.89	-1.15
	(9.07)	(5.83)	(7.63)	(11.58)	(4.69)
Monthly	25.02	-8.07	-13.66	-16.81	11.71
	(9.01)	(6.60)	(10.62)	(12.13)	(4.52)
Rarely	18.17	2.44	-4.63	-11.23	8.35
	(9.46)	(8.27)	(10.19)	(11.95)	(4.97)
Use at home					
Daily	-7.47	-47.37	-15.94	0.29	3.71
	(14.01)	(27.12)	(24.44)	(28.44)	(9.84)
Weekly	-9.91	-45.80	-16.04	1.24	2.56
	(15.61)	(29.48)	(35.77)	(24.99)	(10.09)
Monthly	4.41	-34.47	-5.77	-37.10	8.81
	(15.69)	(28.87)	(40.04)	(30.53)	(9.97)
Rarely	-1.74	-54.28	-19.15	-47.52	2.44
	(14.69)	(34.90)	(40.25)	(31.14)	(11.44)
Use "elsewhere"					
Daily	-31.66	-38.81	-18.71	-4.70	-30.55
	(14.77)	(13.43)	(12.16)	(24.22)	(5.30)
Weekly	-12.95	-21.12	10.15	6.77	-20.86
	(8.07)	(8.00)	(8.10)	(13.73)	(3.94)
Monthly	2.60	-3.06	26.55	4.99	-2.70
	(7.33)	(8.62)	(10.29)	(11.53)	(3.85)
Rarely	7.38	7.12	5.87	6.81	2.84
	(7.13)	(7.24)	(9.64)	(7.64)	(3.99)

Table 6. *Consistency of effects in PISA 2009*

Treatment	Korea	Uruguay	Thailand	Canada
Binary use of computer	51.14 (7.63)	22.43 (5.07)	25.74 (8.51)	65.57 (9.40)
Binary use at school	10.44 (5.81)	7.06 (4.71)	26.45 (6.76)	31.54 (4.35)
Binary use at home	53.14 (5.75)	15.89 (4.44)	24.31 (4.73)	34.80 (4.45)
Daily use at home	35.66 (18.24)	-17.19 (5.60)	15.39 (9.34)	-17.83 (7.79)
Weekly use at home	71.07 (18.58)	-21.38 (6.03)	24.68 (8.12)	-12.41 (8.15)
Monthly use at home	42.25 (23.28)	-9.78 (7.65)	16.32 (8.19)	1.23 (9.48)
Daily use at school	-47.73 (10.31)	-14.87 (5.12)	5.32 (7.07)	-25.93 (5.01)
Weekly use at school	-19.40 (6.33)	-14.16 (4.82)	12.94 (5.95)	-5.48 (4.73)
Monthly use at school	-15.56 (5.50)	3.47 (5.09)	14.76 (6.20)	10.97 (4.81)

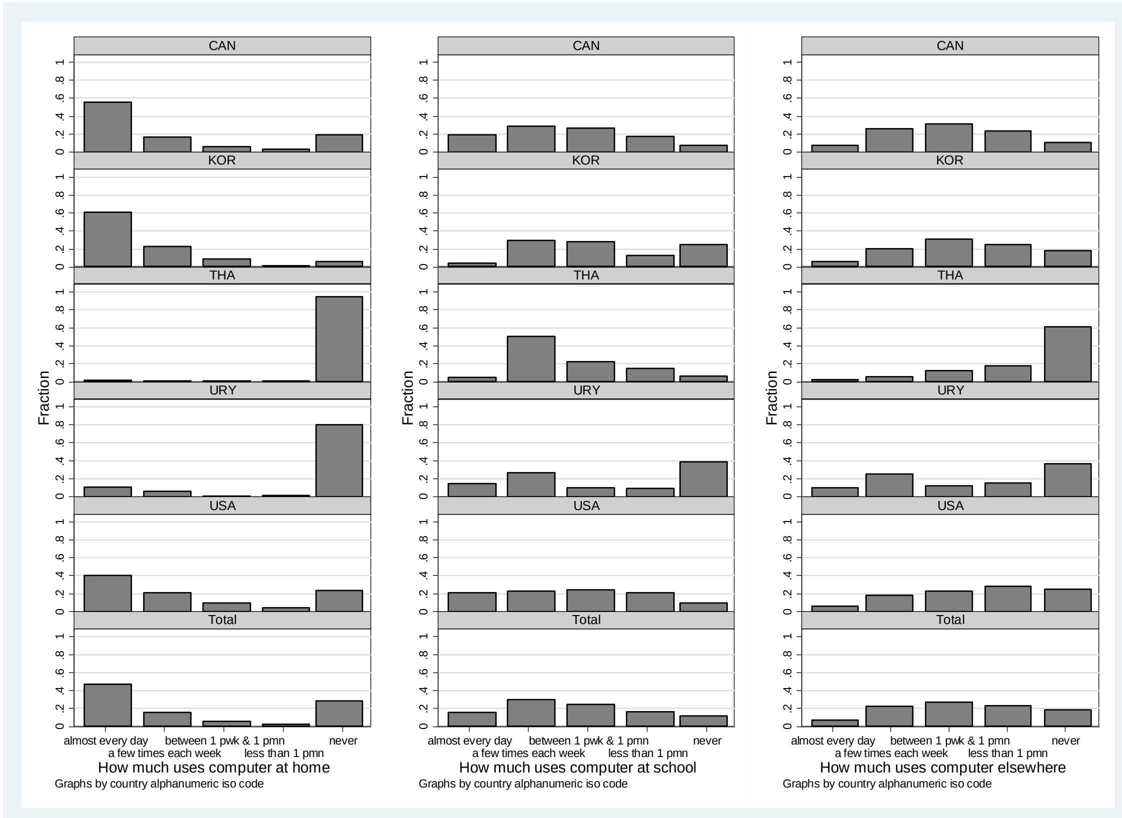

Figure 2. Reported treatment level by country and place of use.

Table 7. *Variables list: PISA 2003 and PISA 2009*

Variable	Original Name (if different)	Label	Format	Values
Outcome variables				
Pv*prob		Plausible value in problemsolving	F9.4	Plausible value in problemsolving
Treatment variables				
Usecomputer	ic02q01	Uses computer	F1	0=No, 1=Yes
Usehome	ic04q01	How much uses computer	F1	1=Almost every day at home 2=A few times each week 3=Between 1 per week and 1 per month 4=Less than 1 per month 5=Never
Useschool	ic04q02	How much uses computer at school	F1	1=Almost every day 2=A few times each week 3=Between 1 per week and 1 per month 4=Less than 1 per month 5=Never
Useelsewhere	ic04q03	How much uses computer elsewhere	F1	1=Almost every day 2=A few times each week 3=Between 1 per week and 1 per month 4=Less than 1 per month 5=Never
Matching/control variables: home/family student				
Escs		Index of socio-economic and cultural status	F10.5	Index of Socio-Economic and Cultural Status
Mothered	st11r01	Mother's highest schooling	F1	1=None 2=ISCED 1 3=ISCED 2 4=ISCED 3B, C 5=ISCED 3A
Fathered	st13r01	Father's highest schooling	F1	1=None 2=ISCED 1 3=ISCED 2 4=ISCED 3B, C 5=ISCED 3A
Posscomputer	st17q04	Possesses computer	F1	0=No, 1=Yes

Posssoftware	st17q05	Possesses software	F1	0=No, 1=Yes
Possinternet	st17q06	Possesses internet	F1	0=No, 1=Yes
Compathome	ic01q01	Computer at home	F1	0=No, 1=Yes
Compelsewhere	ic01q03	Computer elsewhere	F1	0=No, 1=Yes
Famstruc		Family Structure	F1	1=Single parent family 2=Nuclear family 3=Mixed family 4=Other
Hisei		Highest parent occupation status	F2	Highest parental occupation status
Pared		Highest parent education	F2	Highest parental education in years of schooling
Matching/control variables: student				
Stu_id	stidstd	student id	A5	student identification
Sch_grade	st01q01	Grade in school	F2	Student's grade
B_month	st02q02	Birth month	F2	Student's birth month (01-12)
B_year	st02q02	Birth year	F2	Student's birth year (86-90)
Age		Age	F5.2	Age of student
Grade		Grade compared to country	F2	Grade compared to modal grade in country
Gender	st03q01	Female	F2	0=Male, 1=Female
Intuse		Internet/entertainment use	F9.4	ICT: Internet/entertainment use (WLE)
Prguse		Program/software use	F9.4	ICT: Programs/software use (WLE)
Routconf		Confidence on routine tasks	F9.4	ICT: Confidence in routine tasks (WLE)
Intconf		Confidence with internet	F9.4	ICT: Confidence in internet tasks (WLE)
Highconf		Confidence with high-level tasks	F9.4	ICT: Confidence in high-level tasks (WLE)
Comptime	ic03q01	How long used computer	F1	1=Less than 1 year 2=1 to 3 years 3=3 to 5 years 4=More than 5 years
Complearn	ic08q01	Where learned computers	F1	1=My school 2=My friends 3=My family 4=Taught myself 5=Others
Intlearn	ic09q01	Where learned internet	F1	1=Don't know how to use 2=My school 3=My friends 4=My family

				5=Taught myself 6=Others
Matching/control variables: school				
Schoolid		school id	A5	school identification
Compatschool	ic01q02	Computer at school	F1	0=No, 1=Yes
Matching/control variables: national				
Country		Country	A3	three-digit country identifiers
Cnt		alphanumeric iso code	A3	three-digit country identifiers
Subnatio		adjudicated sub-region	A4	four-digit identifier of regions within countries
Weight variables/identifiers				
W_fstuwt		student final weight	F9.4	student final weight
Stratum		stratum	A5	Stratum indicating within-country region

CHAPTER III

WHAT CAN COLLEGE DO?: SOCIAL, CULTURAL, AND TECHNOLOGICAL CAPITAL IN BRAZILIAN HIGHER EDUCATION

Motivation

Engineers are sought after as the catalysts for nations' economic sustenance and growth. However, there is little conclusive evidence as to what educational inputs are directly connected to training better engineers. Indeed, there is little data at the college level in any country, including the United States, to explain what colleges do to effectively increase the achievement of graduates in any field. Recent advances in nation-wide university assessments in Brazil offer a way to concretely answer the question plaguing national policymakers worldwide—what should universities invest in to create essential human capital for a competitive global knowledge economy?

The most important advancement in the field of higher education policy analysis is the growth in the availability of data on student performance at the college level. The first large-scale dataset of this sort come from Brazil; it gathers nationally representative information and includes a general and subject-specific knowledge assessment. I use these data here, in one of the first quantitative studies to estimate the predictive power of home and school factors for student achievement at the college level. I exploit the capacity of the national dataset from 2005 and 2008, using student- and institution-level background factors for a representative sample of students graduating from tertiary degree programs. In doing so, I offer a major contribution to the understanding of formal tertiary education by demonstrating its impact on student achievement.

Engineers are upheld as keys to a country's growth and prosperity. In the United States, President Barack Obama re-established the Council of Advisors on Science and Technology (PCAST), repeatedly turning to them for reports on education as job preparation. (See, for example, one of the more recent reports—Prepare and Inspire: K-12 Education in Science, Technology, Engineering, and Math (Stem) for America's Future [PCAST, 2010].) His 2011 State of the Union speech even likened the current engineering workforce crisis as this generation's "Sputnik moment" (Obama, 2011). The OECD further recognizes the change in economies' structures to the new "knowledge economies", which draw largely on national innovation and engineering capacity (OECD, 1996). The World Bank Institute has gone a step further and quantified a "knowledge economy index", which includes factors relevant to engineering education: innovation, education, and ICT (World Bank Institute, 2007). This translates into huge budgets focused on the training of engineers.

However, even the world's largest economies deplore their continued lack of trained engineers. A recent editorial in one of São Paulo's largest newspapers lamented "A falta de engenheiros [The lack of engineers]" (O Estado de São Paulo, 2012). A focal point of President Obama's recent address to the National Governors Association focused on the need for highly technically skilled workforce (Obama, 2012).

Research Question

In my study, I use a unique new dataset to quantify the predictors of engineering student achievement in higher education. I exploit the capacity of information from

Brazil, which provides student- and institutional-level background factors as well as a general and subject-specific assessment for a representative sample of students graduating from tertiary degree programs. I use these novel data to test the significance of teacher and university characteristics in predicting achievement as well as the importance of home background compared to school factors. I ask here:

"What institutional and student-level qualities are associated with higher achievement for engineering students in Brazil?"

More specifically,

- Does the availability of more physical plant resources, often noted as necessary for engineering training, predict higher achievement?
- Do student-centered learning methods predict higher achievement?
- Does having instructors with actual engineering experience predict higher achievement?
- Do home background factors predict higher achievement, and how do they compare on balance with significant institutional characteristics?

Hypotheses

I hypothesize that learning methods and teacher practices are significantly positively related to achievement on the general assessment and, even more, in subjects specific to engineering. I hypothesize that the availability of physical resources and the certification of teachers will not be as strongly linked to higher achievement as to matters of pedagogy and people. I also hypothesize that the school-based factors will account for more of the variance than home-based factors; I believe the data here will show that a strong selection mechanism related to home background factors is in place prior to matriculation into tertiary education.

Conceptual Framework and Literature

At a time when engineers are called upon to address the "Grand Challenges" of the 21st Century (National Academy of Engineering, 2010), the cross-sectional picture my work provides is a novel and prescient perspective in the nascent field of engineering education (EE) research. To provide an overall context for the study of engineering student achievement, I describe the substantial debates surrounding the numerous predictors of student achievement, both in and outside formal schooling institutions. Literature using large datasets to investigate achievement in higher education is scant, however; I give a broad overview of that subject area here. I also note previous work in Brazilian higher education and in engineering student training.

As policymakers tweak the engineering pipeline, there is some consensus on the broad domains that are important: physical/laboratory resources are costly but necessary inputs that are vital for engineering achievement; practical learning opportunities are beneficial as replicas of real-world job tasks; and, having teachers who know a thing or two about real-world engineering themselves makes it easier to transfer useful experiences to the next generation of engineers. But, beyond policymakers' intuition, there are few quantitative analyses of which of these inputs matter, let alone estimates that approach an understanding of the causal process that leads from a child's home to her graduation day with an engineering degree. One of the main hindrances has been the lack of data that could answer these questions. However, the question of whether school matters for student success has been addressed numerous times and in numerous contexts for primary and secondary schooling.

The Effect of Home and School on Academic Achievement

Primary and secondary education. National data on student performance in primary and secondary education have existed for decades. Some school factors (e.g., class size; teacher experience in the first few years; the availability of textbooks) have been shown to matter. At the same time, factors outside the school, in contexts around the world, find a way to enter the hallowed walls of the learning environment. A student's home environment prepares her to be able to navigate the pathways of formal schooling (see the large literature on social and cultural capital; Bourdieu, 1977). Both the school and the experiences a student has outside of school affect how that student scores on tests from pre-primary school through high school.

Among numerous unsettled debates is how much either of these environments matter for what policymakers point to as the key end-of-the-day goal: academic achievement. Educators, policymakers, parents, and students alike believe in the power of formal schooling institutions to promote student learning and open opportunities for any student willing to avail herself of learning resources. However, a number of studies have called into question the "power" of schools in the face of hugely influential home background factors. While factors of the schooling environment should be related to the learning outcomes of students, their educational preparation begins outside of the school and continues there throughout the child's educational career. Numerous students have been undertaken to understand the relationship between numerous characteristics of the environments around a child and his or her academic achievement.

Beginning with the Coleman Report in the United States (Coleman et al., 1966), a series of studies showed that home resources explained more of the variation in scores than the inputs a student was exposed to in school. However, when studies were expanded to include a number of lower-income countries in the analysis (Heyneman & Loxley, 1983), school resources explained more of the variance in achievement outcomes. In some contexts, the inputs of formal schooling—textbooks, desks, teachers—seem to outweigh the advantages or limitations that students bring to school (e.g., Uganda; Heyneman, 1976); in others, a student's personal characteristics are overpoweringly predictive of achievement, regardless of what school resources they can access (e.g., United States; Coleman et al., 1966).

Follow-up studies continue to replicate this line of work in varying sets of countries. A heated debate continues around the question of how much school "matters" and where this is the case. Gamoran and Long (2008) provide a useful comprehensive review of the development of this area of inquiry over the last forty years, including a description of the study of these two sets of resources in the international domain (e.g., Baker, Goesling, & LeTendre, 2003; Long, 2006). They reiterate the fact that, in lower-income countries, school resources explain more of the variation in achievement (Gamoran & Long, 2008). More recently, authors (e.g., Chudgar & Luschei, 2009) have tried to better understand why school or home factors matter more.

In this vein of literature on school and home background effects, numerous explanations are offered for the varying influence that these factors display on educational achievement. Students in environments where schooling is nearly universal are more differentiated by the resources they have to prepare for learning outside of school; conversely, students in places where educational resources are scarce, and where advancement depends almost entirely on test performance, are more differentiated by the quality of school resources they have (Heyneman & Loxley, 1983). Countries with greater inequality may see schools serve as a way for children from different backgrounds to have a more equal opportunity to learn important academic subjects (Chudgar & Luschei, 2009). It has been established, though, that the school environment and the platform of the home interact to position the student to achieve on a test, and policymakers can find policy tools to tweak a student's *resources* at home and school to support educational development.

Various studies point to the perceived importance of specific factors within universities such as student funding, remedial courses, science equipment, teaching practices, and professor experience for tertiary students (ABET, 2011). However, the outcomes of interest in these studies are usually persistence, attainment, or degree completion (National Science Board, 2012). The questions of what factors can improve students' performance on a standardized test have largely been asked in the primary and secondary school context. Once students get to college, will their background matter at all? Or will the elite few who have "chosen" to pursue an engineering degree check their "invisible knapsacks" (McIntosh, 1988) at the door and be separated only by the quality of the learning materials at their disposal?

Achievement in higher education. The dataset used in this analysis is one of the first opportunities to look at student achievement in a higher education context. While student test information has long been and is increasingly a staple of primary and secondary educational studies (e.g., No Child Left Behind, the *bac*, the *arbiter*, TIMSS, PISA), tertiary data is far behind. Information is usually contained within institutions, and even then, this information is usually limited to course grades (or GPA) or unique focused studies, rather than a broadly comparable, nationally-standardized test.

In the near future, the Organisation for Economic Co-operation and Development (OECD) will conduct a new assessment, the Assessment of Higher Education Learning Outcomes (AHELO), which will begin to fill in this dearth of information. AHELO will test general skills (e.g., critical thinking) and discipline-specific skills besides gathering demographic and educational environment information; the study is still in the feasibility testing phase, and engineering is one of the disciplines at this stage (OECD, 2011). University and non-school factors will be available to researchers to analyze for students in their final year of undergraduate programs in OECD and OECD partner countries. This information will be available for chosen example institutions in 15 countries at the end of 2012. However, Brazil has administered a standardized assessment to a nationally representative sample of university first years and final years.

The Exame nacional de Desempenho de avalição de Estudiantes, or, the National Student Performance Exame (ENADE), grew out of a demand for standardized measures of higher education performance. Beginning with the Provão, Brazil attempted to provide a nationally-standardized measure of institutional quality (Cruz et al., 2010). The Provão provided information on student course performance, teacher variables, and institutional factors and generated a score used for comparison (and competition). ENADE, which grew out of the Provão, added a student sampling process and a curricular- and criterion-based examination. ENADE has been administrated yearly since

2004, though every year does not comprise every subject area. The test gathers information on general knowledge (e.g., civics and Brazilian history) and subject-specific knowledge for a sample of enrolling (first-year) and completing (final-year) students. (The first- and final-year students take the same test.) ENADE also includes student background questions and university and course resources. Other assessments conducted under the Brazilian Institute for Higher Education (e.g., the *Censo da Educação Superior*, or Higher Education Census) provide additional information on courses and students.

Despite the potential of the ENADE dataset, few studies have taken advantage of it, possibly because of its recent availability and ongoing development. I note the few examples here. Cruz and coauthors (2010) use ENADE's information to investigate the link between quantitative reasoning classes and performance on the ENADE exam. The authors use correlation coefficients to answer this question for a sample of Administration students. While I build on their work by including curricular information as one of the institutional factors associated with ENADE performance, I use a regression model that includes other institutional factors and student-level controls. I build on another available study as well (Lobo & Lobo, 2010). The authors investigate the factors predicting the performance of engineering students from 2005, including both cultural background factors and academic behavior, which are shown to have significant predictive power. They follow up by predicting the performance of final-year students in Administration based on the quality of incoming students for that course (for the same year); first-year student performance explains 20% of the variance in final-year performance, though this is in a simple univariate regression.

In addition to academic behavior and home environment, I control for individual student factors that previous studies with ENADE have found to be significant. For example, Vendramini and coauthors (2010) look at statistics questions for the entire sample of students tested. The authors find differences in performance by gender for a number of sub-samples of students (e.g., Pharmacy, Dentistry). The authors also note differences in general performance between students in different majors, pointing out that there are important differences in competitiveness for the students who go into different fields. Since I concentrate on engineering, I may not find this difference.

One exemplary paper is available that uses ENADE data to investigate the effect of peers in student school choice and the setting of tuition prices (Andrade et al., 2009). Of particular use is the methodology employed in this paper. The authors use freshman performance on the ENADE as a proxy for student body quality; I employ a similar approach in looking at the growth in test scores for cohorts of students in the same institution. Further, the authors check the robustness of their results with a 2SLS estimate and with the addition of data from other datasets; I verify the consistency of estimates in a similar fashion.

The Brazilian Context

Race and inequality in Brazil. The scant amount of previous work using ENADE does not address the pressing question of whether students' backgrounds largely determine the probability of their academic success or whether school resources at the college level can mitigate pre-university disparities. In Brazil, these disparities are large. Even for the subset of students who make it into college engineering programs, differences in income, race and ethnicity, gender, and parental education are significant.

And, this is indeed a select group.

Brazil is marked by high income inequality, which is observable in the ENADE dataset as well; most of the students fall into the lower brackets of the categories on the questionnaire, with the portion of students falling off rapidly as income increases. The portion of the population below the poverty line varies from 23-45% based on the level used and is concentrated in rural areas, smaller towns, and the North and Northeast regions (Ferreira et al., 2003). And, this income inequality is closely intertwined with access to educational opportunity; a study in rural Paraíba found that educational attainment was the most important factor related to poverty level (Verner, 2004).

Brazilian policymakers have looked to the formal schooling system not only as an institution that can mitigate home inequities, but as a playing field that itself needs to be made more equal. Earlier efforts at alleviating poverty initially exacerbated inequalities by supporting the relatively better-off, but its more recent progressive policies and socially-inclusive market interventions (Hunter & Sugiyama, 2009) have been accompanied by greater poverty reduction, though slower growth, than India (Ravallion, 2009). Targeted interventions—for example, conditional cash transfers—have a positive effect on school attendance for children from poor families (Cardoso & Souza, 2004). The “Bolsa Escola” and, later, “Bolsa Familia”, both targeted education-related family stipend programs; however, they did not necessarily translate into educational benefits besides increased attendance (Schwartzman, 2005).

Similar to the United States, socioeconomic opportunities differ greatly across racial and ethnic lines (Trumpbour, 2011). One of the most complex out-of-school factors investigated here is race and ethnicity. Brazilian society has historically claimed to be “color-blind”, but developments in the 20th century led to a more complex understanding of the numerous races in the country. After the 1960’s, the Black Movement in Brazil, spread in part from the United States across the Americas, focused on empowering the black identity by pushing the multi-racial categories aside as an “escape hatch” (Daniel, 2004) and focusing on empowering the most disenfranchised groups. The conversation around race has continued to develop since then.

Brazilians, in fact, recognize a large array of racial designations; the Brazilian census has over one hundred self-designations, which are mostly based on phenotype (Brown, 2011). Alternatives to the Brazilian Census Bureau’s designations that have been vetted have not been shown to be less complicated (Miranda-Ribeiro & Caetano, 2004). Self-classification is reported in numerous places to be related to SES and gender as well (Francis & Tannuri-Pianto, forthcoming), though the landscape shifted with the introduction of racial quotas. A study incorporating both surveys and interviews in Belo Horizonte found a decrease in self-designations of “white” and an increase in designations such as *negro* (black), *amarelo* (yellow), and especially *moreno* (brown), also noting that it is not just lighter skin, but a greater number of possessions that predicts self-designation as “white” (Brown, 2011). Identity in this context is mutable; depending on one’s own perspective and possession of certain types of social capital, an individual assigns herself a racial category. In my investigation of technological capital, a student’s self-concept in relation to technology and technological careers plays an important role in navigating the higher education system.

Higher education in Brazil has long been considered elitist, though it has not explicitly excluded non-white students (Silva, 2007). From the time of colonialization, a “racial hierarchy” was in place in Brazil, a rigid social structure connected to economic opportunities that continued even into the era of the “myth of a racial democracy” (McLucas, 2011). Recently, even the “colorblind” Brazilian system has recognized the inequality in educational opportunities for different races, in particular at the tertiary level. After the turn of the century, a controversial racial quota system began rolling out at different universities, bringing with it a wave of protests and legal challenges (Duffy, 2009). Student protests, an established and accepted part of Brazilian higher education, were this time directed at an attempt to enhance equity of access, including in engineering. Studies of social activism in Brazil in general point out that even supposedly democracy-enhancing mechanisms such as protests may be used by those already in possession of social capital to preserve their privileges (Hunter & Sugiyama, 2011).

Quotas are still in place, though. A study at the University of Brasília found that initially there were significant differences in admittance cutoff scores for students admitted under the quotas, but this narrowed after only a few years as “darker” students’ preparation for school increased (Francis & Tannuri-Pinto, 2011). (In my dataset, ENADE, there is a significant difference between minority and white students in entrance exam tests, but this difference becomes insignificant when controlling for other important demographic and institutional characteristics.) Further, differences in grades once at school were practically small; the authors also noted, though, that there were changes in self-designations—for example, “brown” students were more likely to consider themselves “black” as a polarization of racial identities took place (Francis & Tannuri-Pinto, 2011). Even for younger children, affirmative action policies may be related to more diverse, “darker” identity designations, though all of the children studied would prefer to be “whiter” (França & Lima, 2011).

Race and class are closely intertwined in the Brazilian context. Brazil has a notably high level of inequality, accounting for the lion’s share of the poor in Latin America (Elbers et al., 2004). As racial identities were largely eschewed in the “racial democracy” prior to quotas, they have been difficult to incorporate as important dimensions of social policy. Researchers find that current racial quotas are understood as class-based justifications, as class “cleavages” are still prescient for individuals and seen as within the purview of the state to address. Even though policies explicitly addressing race are now being realized, they are still understood mostly through the intersection with social class (Schwartzman & Moraes, 2010; Lovell & Wood, 1998).

Brazil’s higher education system. The Brazilian context is large and diverse, and it poses a host of challenges that are unique to this dataset. The private sector in higher education is very large, especially the for-profit area, but the student selection into the highly competitive public schools creates a stark contrast in the reputation of graduates from the two sectors. A complex environment of race and ethnicity, sex, high income inequality, and the urban/rural divide complicates the expected relationships between school inputs and student achievement.

Brazilian higher education is dominated by private universities, which make up over 70% of the institutions by administrative category (Paranhos et al., 2009), many of which are for-profit universities. The private sector in higher education has grown immensely in the number of institutions and in the size of the universities, aided both by “neo-liberal” World Bank and government incentives (Wang, 2011) as well as by the huge increase in demand for higher education (McCowan, 2004). While the private sector offers less competitive entry exams and flexibility in schedule and location, the private sector may actually be contributing to an increase in inequity, as fees are beyond the reach of a large portion of the age cohort and are higher for better institutions and more rewarding majors (McCowan, 2007; McCown, 2004).

Before entering a tertiary program, students must have already selected their field of study, and they apply to institutional programs specifically in these areas. The admittance system to higher education is complex and linked to a high-stakes test required of high school graduates wishing to enter a particular university program. In the past, a student would have to choose her desired major and desired university and take that university's specific *vestibular* exam, an admittance test that differed by each university program. More recently, universities are standardizing their exams in the form of the ENEM (High School National Exam), saving costs for students and universities alike (Downie, 2010). Its implementation continues to be controversial, and universities such as Universidade de São Paulo (USP) and Universidade de Campinas (UNICAMP), some of the most prestigious universities in the country, continue to prefer their own tests and schedules. Many students in the ENADE dataset can be linked to their ENEM score, though, which provides an important check of the consistency of estimates as a pre-test score.

Engineering education. Concerns abound regarding recruiting more engineers and holding them in the discipline. Talent and skills are highly sought after by employers. An international poll of human resource managers in 2006 found that three-quarters said that attracting and retaining talent was their top priority; some 62% worried about company-wide talent shortages (Wooldridge, 2006).

At the same time, a broader awareness of world issues and international experience have become more desirable for students and future employers alike (Continental Corporation, 2007). A huge number of students are studying abroad (OECD, 2007). Engineers are being called upon to answer global challenges; certain questions, e.g., climate change, point to globalized problems as well as solutions. Research can no longer be confined to certain locales, especially in science (Young et al., 2006).

"Grand challenges" in engineering point out the potential for engineering to solve major problems for the world. Many of the challenges are pressing issues for development (National Academy of Engineering, 2010). Growing and changing demands on engineering graduates have made the skills needed a more complex field to navigate. The United States, for example, adopted new accreditation criteria that call for student-centered pedagogies and preparation in soft skills; a National Academy report outlines new skillsets needed for the "Engineer of 2020"; and a survey of college administrators and employers corroborates this (ABET; NAE, 2004; NACE, 2004). Students are looking for professors who would deliver and possess these same skills (Morell & DeBoer, 2011). This study complements the extant literature by estimating the effect of both university and home background factors on engineers' achievement.

Engineering education in Brazil. Brazil's technology sector has developed largely within its own sphere. The nation is isolated as a Lusophone country in a largely Hispanophone area; regionalization efforts in engineering have faltered before (Scavarda, Morell, and Jones, 2006). While the last half of the 20th century saw notable growth in science and technology capacity in Brazil, the sector has not had resources keep up or solidified connections with the government and the education system in the last decade of the century (Schwartzman et al., 1993).

As Brazil industrialized, its engineering identity was largely characterized by fragmentation at the regional and municipal levels—by a complex “agglomeration of regional economies…looking outwards” and by strong municipal organizations (Lucena, 2008, p. 3). Even now, strong regional differences in higher education are notable. Brazil’s first emperor, who recognized the nation’s vast and diverse resources needed to be mapped, tried to structure engineering as a nation-building tool; engineering universities were originally modeled strongly after France, though with local modifications, and schools still today struggle to balance practical and theoretical teaching (Lucena, 2011). I recognize the historical context by controlling for institutions’ locations and their position relative to students’ homes. I also investigate the importance of practical and theoretical teaching methods.

Though national innovation policy encourages investment, many Brazilians studying abroad return home, and though higher education continues to expand, it still has a drought of engineers (Carlson et al., 1996). Brazil’s higher education system is influenced both by former colonial occupiers and the huge EE system in the USA (Castro, 1983). Referred as a “natural knowledge economy” (Bound, 2008), Brazil’s rich natural resources are a national asset and a sustainability challenge for local engineers. Engineering needs may go unmet because of a mass exodus during undergraduate training, when many engineering students change to less challenging majors, possibly because of the difficulty of the course (Birdsall & Sabot, 1996). Despite the high level of prestige of engineering as a field of study, students drop out or avoid choosing the field altogether, and only recently have researchers begun to address the engineering education system as a policy lever.

In the last forty years, science education research has been systematized and developed as the overall science education field was renovated (Villani et al., 2010). In Brazil, student-centered approaches such as problem-based learning (PBL) have been evaluated and shown to be successful in engineering courses (Roberto, 2008). Brazil is developing high-technology R&D centers and advanced technological capacity, with biomedical engineering education and research growing notably over the last ten years, for example (Gehlot, 2009). Some universities (particularly new ones) have successfully experimented with non-traditional courses such as broad "Introduction to Engineering" courses which allow students more time to consciously choose their discipline (Romero et al., 2011). With the development of private education, policymakers across Latin America are struggling to determine how engineering still relates to society as the field shifts away from infrastructure and nation-building support (Lucena et al., 2008).

As a fast-developing middle-income country, Brazil is investing heavily in the preparation, training, and growth of the engineering workforce. It recently announced a new US$2 billion scholarship program to support science and technology students as part of the larger "Science without Borders" government program (Gardner, 2011). And, Brazil is not alone in this. Around the world, urgent conversations and concrete investment make STEM education a high priority. The results of this study have broad global implications. Little rigorous evidence exists—for any higher education system worldwide—to determine where in the university environment policymakers should focus, or even whether it is the university system and not K-12 education or even non-school interventions where the money should be directed. Brazil is in the position, though, to provide the data that can finally answer this question. I analyze those data here.

Data

The ENADE data are gathered yearly for a representative sample of students in selected institutions in their first year or last year of a selected program. ("First years" have completed 7-22% of their coursework, and "final years" at least 80% of their coursework [Ministério da Educação, 2005].) In 2005 and 2008, engineering institutions participated in the ENADE data collection. ENADE assesses both general knowledge, such as Brazilian history, and subject-specific knowledge questions on engineering for students in the major. Besides the assessment component, inspectors visit the universities to examine physical, pedagogical, and human resources. Students also provide home background information. I limit my sample to students whose listed area of study is any "Engineering" (Engineering I-VIII) for 2005 and 2008 test-takers; I have over 45,000 observations for each year.

Since standardized assessments of tertiary student achievement are nearly non-existent at the national or even state levels, researchers and policymakers are very excited about the upcoming release of the Assessment of Higher Education Learning Outcomes (AHELO). Compared to ENADE, AHELO has the advantage of comparing results across countries. However, it is currently only in the feasibility testing phase; information will not be available even for "example institutions" until the end of 2012. ENADE, on the other hand, has nationally representative data on both general and subject-specific areas, and it also gathers student and institutional background information. Further, information is only being gathered on final-year students, not first-years, while ENADE covers both cohorts. Testing culture has shifted in Brazil as well, with universities slowly adopting more nationally-standardized assessments for entrance exams as well as for institutional evaluation. Both of these assessments are critical to furthering policymakers' understanding of the role of higher education institutions. The detailed relationships between resources and achievement that ENADE can illustrate are important complements to the broad pictures AHELO data will paint. Future development for AHELO could build off of lessons learned in ENADE.

Supplemental Datasets

I divide my analyses into two sections (see methods below). My main analysis is completed on two years of full ENADE data for students in 2005 and 2008. I take advantage of additional available information, though, for checks of consistency of the results I find. The second component of my analyses matches the majority of students in 2005 with their college entrance exams and more detailed college information. First, I match students in the 2005 ENADE sample with those who took the ENEM (Exame Nacional do Ensino Médio, or National High School Exam). For the students in this matched dataset, I further add data from the Higher Education Census. Not only can I get inside the "black box" to understand the specific resources of institutions that matter, I can control for pre-college achievement, match this for first years, and incorporate important student-level factors such as the distance from the student's home to the college. (In Brazil, students are much more likely to live at home and/or to attend university close to home.) I have ENEM data back to 1999, and using these data along with the 2005 university census, I create a matched dataset of nearly 60% of the ENADE sample.

Variables

I use only ENADE data from 2005 and 2008, when engineering students were assessed. Follow-up analyses may use 2011 when it is made available. I further limit my sample to students in the 8 "groups" (7 in 2005) of engineering study. These include civil, electrical and electronic, mechanical, chemical, material, industrial, geological, and agricultural engineers and their related fields. I use information from the student background questionnaire (age, gender, first/final year, race/ethnicity, etc.), the student assessment (both general and subject-specific), and the department representative's questionnaire on characteristics of the program.

Both student-reported and administrator-reported information on university resources are available. While administrator information might be considered more "objective", it should be noted that respondents for the administrator questionnaire are course coordinators at the same universities, and these scores are part of the overall scores assigned to the universities. I note differences between student and administrator reports.

Outcome of interest. I run analyses on the full assessment as well as the general knowledge and engineering-specific tests separately. The outcomes of interest are relatively normally distributed in both the full 2005/2008 dataset and the matched 2005 sample. In 2005, the average scores are slightly lower.

Student background. The characteristics of the individual student, the student's home environment, and the pre-college learning environment are combined in the construct of "student background". Race in the student questionnaire is given in the categories (translated) "white", "black", "mixed", "Asian", and "indigenous". Experience with private school prior to university is operationalized as "1" if the student has had any exposure to private education (some or all). Student reports of computer and English proficiency are used as proxies for prior ability (highest levels) and reported study time as a proxy for academic press (logic model). Student questionnaires also give information on parental education; the higher of the two for parents' education is used and compared to the baseline category of "no education". The same questionnaire also provides income information. (See figures 1 through 4 for the distribution of parental education by income levels and the distribution of family income by type of university.)

Physical resources. Physical school resources include metrics relevant to the whole institution and resources specifically devoted to STEM fields. The dataset provides information on student evaluations of laboratory quality and the institution's overall lab area. Data are also acquired on average class size and student teacher ratio. (See tables 9-13 for details on institutional characteristics.)

Teacher quality. Student perspectives are given on teacher quality as well as quantitative measures of teacher qualifications. Teacher experience is reported by students as "teacher mastery of subject taught", while the ratio of PhDs to the overall faculty is given by the institution.

Pedagogy and learning environment. Classroom pedagogy is reported as one of the following primary methods of instruction: "lecture", "partial lecture", "practical", or "group work", compared to "other". Student evaluations of resources are averaged within programs, and data can be matched for program-level resources in the restricted dataset as well.

Missing data. There is some missing information in this dataset, particularly for the student questions on the background questionnaire. However, it does not appear to be systematic. I nevertheless use multiple imputation with chained equations to address potential bias from casewise deletion of a sample of the dataset that is not Missing Completely at Random (MCAR) as well as to increase the efficiency of my estimates. (Rubin, 1987 shows that even with a rate of missing information of 0.5, five imputations will yield estimates over 90% efficient.)

Methodology

I first estimate a basic OLS regression predicting student achievement using student-level controls (age, gender, parental education). I predict achievement for final year students based on these individual controls as well as institutional resources, teaching practices, and teacher qualifications. Previous research suggests that there is an endogeneity of student choice in the relationship between school quality and student achievement, and I test a number of additional models to determine whether estimates are consistent. I find evidence of the endogeneity of student choice, but I find that the general findings are consistent across models. I estimate a model that utilizes a fixed effect for each engineering program. I estimate the portion of variance in achievement within and between institutions. I am also able to match some students to their entrance exam score and control for the students' achievement prior to college, isolating the effects of institutional inputs. Finally, I take advantage of the multiple years during which engineering students were assessed by comparing the scores of first and final year students.

I run a number of analyses on the information provided by the ENADE data. First, I look at the confidence intervals for the in- and out-of-school factors predicting achievement of the first- and final-year engineering students. I use conventional (alpha = 0.05) levels for creating the confidence intervals for the coefficient estimates. I also check the consistency of the estimates between the numerous models I estimate. If there are major differences between the basic OLS estimate and the IV and fixed-effects estimates, I attempt to account for this. Finally, I look at the decomposition of variance in the prediction of student achievement outcomes to understand the percent of variation explained by home versus school factors. I split my analyses into two sections: full samples of 2005 vs. 2008 and checks of consistency with the 2005 sample for which I have location and pre-test information. (Note, I only have pre-test information for the matched sample, so I look at a standard value-added model only with these data.)

Cohort Data

OLS. I first estimate a basic OLS regression predicting student achievement using student-level controls. I predict achievement for final year students based on these individual controls as well as institutional resources, teaching practices, and teacher qualifications. I use the following general model as my "naive" estimator:

$$Y_{ij} = \beta_0 + \beta_1 StuControls_{ij} + \beta_2 HomeRes_{ij} + \beta_3 TeachQuality_{ij} + \beta_4 SchoolRes_{ij} + \beta_5 ClassRes_{ij} + \beta_6 TeachPrac_{ij} + e_{ij}$$

where

StuControls are the student controls such as age, gender, and study hours;

HomeRes are the home background factors such as parental education and location;

TeachQuality are the teacher quality factors such as experience;

SchoolRes are the physical resources of the engineering institution;

ClassRes are the classroom resources such as class size;

and TeachPrac are the teaching practices such as student-centered learning of student *i* in institution *j*.

FE, RE. I am concerned about student choice in the relationship between school quality and student achievement, even more so in Brazil than in studies in the United States, and I test a number of additional models to determine whether estimates are consistent. I compare the first model to a second that utilizes a fixed effect for each engineering program. The following model is employed here:

$$Y_{ij} = \beta_0 + \beta_1 StuControls_{ij} + \beta_2 HomeRes_{ij} + \beta_3 TeachQuality_{ij} + \beta_4 SchoolRes_{ij} + \beta_5 ClassRes_{ij} + \beta_6 TeachPrac_{ij} + \beta_7 Institution_{ij} + e_{ij} + u_j$$

where each institution in the dataset receives its own error term u.

Cohort Comparisons. Finally, I take advantage of the multiple years during which engineering students were assessed. I compare the scores of first- and final-year students in 2005 and 2008 in the same institutions, recognizing that institutional changes may have been made over this time. I also look at the cohorts of students who were first-years in 2005 and final-years in 2008. (Typical engineering undergraduate degrees in Brazil take at least four years, but I use this cohort study as the closest approximation available.) This is similar to the General Course Index (IGC) procedure, which uses information from the previous three years' ENADE results to evaluate universities across Brazil.

Robustness Check with Matched Data

I incorporate two additional sources of information and re-run the analyses with data from the same students on their pre-college entrance exams and more detailed characteristics of their colleges. I use OLS to estimate the predictive power of school and home resources while controlling for the student's pre-college test score. I use this subsample in a fixed-effects model as well, though I do not need information from the CENSO for this model. I also test an instrumental variables model using distance and tuition to instrument for the easily-visible school characteristics students may identify in their decision-making. Previous studies in higher education in the US (e.g., Bettinger & Long, 2004; Kling, 2000; Card, 1993) use distance between the student's home and the location of the college as an instrument for the student choice mechanism. Some authors argue that this is either not a valid instrument or that interpretations of results are erroneous (Carneiro & Heckman, 2002). However, in Brazil, distance to school is an even stronger predictor of school choice; many students still live at home during college. And, given the other information I have, I am less concerned that distance would be correlated with omitted variables.

Limitations

One of the major limitations of the external validity of my study is the fact that a number of institutions, including some of the most prominent ones, choose not to participate in ENADE. While the number of participating institutions is still large, some of the non-participants are seen as the top institutions in the country (including the Universidade de São Paulo, the top engineering school), universities that do not need to participate in the IGC ranking system since they are already recognized as the best. At the individual level, students choose to boycott the ENADE assessment as well. The majority of these boycotts are done by handing a blank test, and a higher percentage of public school students boycott than those in private school. However, the engineering groups were among the lowest in the proportion of students boycotting, none more than 6% (Leitão et al., 2010).

In addition, there is a popular understanding that, since the ENADE is a major component of the high-stakes institutional ranking of universities, that universities game the ENADE test and send their highest-achieving students to take it (Folha de São Paulo, 2012). One way I can verify whether this threatens my sample is to compare the demographic characteristics of the ENADE sample with the overall characteristics given in the CENSO. As a check, I look at the proportion of females in the matched sample of ENADE compared to the gender ratio of the student body overall given in the CENSO for the same university. I find that the mean female proportion in 2005 given in ENADE is 0.26 (SE = 0.01) while the average gender ratio in the same universities is 0.47 (SE = 0.03), a significant difference. However, even with this variable (the closest comparison I can make between the two datasets), I cannot say for sure that universities are indeed sending a different group of students to take the test; the information I have from the CENSO is on the whole institution, and there should be a lower ratio of females in the engineering programs. I confirm that that correlation between the gender ratio and average female proportion in the course move in the same direction and are significantly correlated (0.29, p=0.00).

Results and Analysis

Student Background

Characteristics of the student’s identity and experiences that pre-date the college years still affect his or her engineering achievement. Depending on the preparation and acculturation students receive prior to college, they are differentially able to learn the material given in the university; they come to university with different tools. These results fit into the established theoretical framework of social and cultural capital (Bourdieu, 1977). Individual factors that are part of the student's identity, her/his home environment growing up, and the experience of elementary and high school have persistent predictive power for a student's achievement at the beginning and end of college. Tables 1-4 give estimates from models that use only the ENADE data. Results are generally consistent in models that use students matched with information from the pre-college exam (ENEM) to have a pre-test score. Tables 5-7 show results using ENADE data matched with ENEM and CENSO.

The student. Results across the models suggest that many components of the student's identity are important for student achievement. Individual background characteristics are more frequently significant predictors and with stronger effect sizes for the engineering component of the test than for the general part, the burden of the traditionally under-represented minorities in engineering that has been identified in other studies. For example, women do significantly worse on the engineering-specific component, though they actually do significantly better on the general component. Black, mixed, and indigenous students have lower scores than white students on the engineering portion. Even using fixed effects to control for selection into better universities, I find that white students outperform their non-white peers; it is not just that privileged, high-performing students choose to attend better universities. As might be expected, students who report that they study more have higher scores, as do students who report that they are better at using computers. These results are consistent between models using only the full ENADE engineering sample and models using ENADE with matched pre-college exam scores as a pre-test.

The home. Parental education and family income matter in predictable ways, but they matter much more for the general component of the test. Even in the model that controls for a student's previous scores, home background still significantly predicts achievement; the cultural capital that the student receives as s/he grows up not only helps to provide the student with knowledge prior to entering college, it also provides the student with the tools used to navigate higher education and learn more while at the university. Having parents with any education—whether just elementary school or higher education—predicts higher scores than having parents without formal education. Coming from a family with a low income (as compared to families in the middle) significantly predicts lower achievement, and coming from a family with a high income predicts higher scores, especially on the general component. Even controlling for selection bias into better schools, students from high income homes perform better on the general part of the assessment.

The pre-tertiary school experience. Students who attended private high schools have significantly higher test scores, particularly on the specific (engineering) part of the assessment. This runs contrary to the college private school effect on scores (more detail in that section below).

University Factors

Even controlling for all of the student background factors and institutional inputs in the model, students in their final year have higher scores than students in their first years. Even in fixed-effects models that include controls for prior achievement, the effect size of being a final year versus a first year is approximately 0.7—assuming a 5 year degree, approximately 0.14 per year. This is even larger for the engineering test—0.16 per year. By the standards given for upper secondary school math gains annually [0.01 in Hill et al., 2007], this would be considered quite large. And, in Brazil, high school achievement effect sizes can be approximated given Brazil's *Prova*, or a standardized test given to 8th and 11th graders—in 2005, the average gain per year in high school was approximately 0.17 standard deviations, not controlling for other factors related to growth (INEP, 2012; Aparecida et al., 2008).

Students are learning *something* during their university experience, and the magnitude of the increase in achievement due to being a final year versus a first year is about twice as big for the engineering test as for the general knowledge test—engineering students are indeed learning something at school about engineering. The factors at schools that contribute to this learning are complex, however, and institutional characteristics do not all behave predictably. Further, in looking at overall achievement, it appears that about half of the variation is at the student level within institutions, and half is between institutions.

Within institutions—even controlling for the first year students' scores, a higher proportion of males and white students predicted higher final year score averages, while higher family income predicted lower scores.

It is illuminating to see the significantly different profiles of the student body that begins the engineering course and the group that graduates, as well as to compare the group that goes through the private university system to the group that goes through the public system. In addition, because I can match students in the ENEM dataset, I can compare the profile of students in the representative group of engineering courses in ENADE and students who were not. Table 8 gives these comparisons. It is clear that the group of students tracked into the private versus the public institutions are different, and it is clear that the students who finish their degrees are systematically different from those who start (Table 14). This difference also helps explain counter-intuitive results we see. For example, in the fixed-effects models, the coefficient on private primary and secondary schooling becomes significantly negative. This may be explained by the group of intense *escolas tecnicas*, highly-regarded public technical schools. Further, we can see that the students who go into engineering are systematically different from their peers who have taken the same college entrance exam. These differences are statistically and practically significant.

Equipment. In one glaring counter-intuitive result, student reports of very good physical facilities—including laboratories—predict lower scores on the engineering assessment compared to reports of good and satisfactory facilities. This may be explained by the conundrum of well-equipped but low-performing private schools. In models using the matched data (and controlling for prior achievement), effects are in the predicted direction. And, in looking at the addition of an instrument to the matched data, the bias in these estimates is clearly diminished. This self-reported data, while problematic if interpreted without further examination, is useful in its revelation of the varying perspectives students have on the resources at their disposal. The students who may be more critical and demanding are also, on average, performing better; on the other hand, students who may accept whatever resources they are given without a critical eye are not doing as well. Further, the students at private schools who are, on average, performing worse report greater satisfaction with the resources they have.

More predictably, large average class sizes are related to lower scores, particularly for the engineering assessment. In the institution-level panel dataset, large average class sizes predict lower scores even when controlling for first year student scores.

Teaching. Student evaluations of their teachers' mastery of their subjects shows that very good teachers and bad teachers both predict lower scores compared to good and mediocre teachers. The negative impact of very good teachers is, however, only marginally statistically significant ($a = 0.05$), and the magnitude of the negative impact of bad and very bad teachers is ten times larger. The counter-intuitive result may indicate that students who are doing well or are at better schools are more critical of their professors, and students who may not be learning more are less critical of their professors. This explanation is expounded upon below in the discussion of private universities.

Private universities. Scores are predicted to be significantly lower in private universities than in public ones (effect size = 0.33). There is a higher proportion of large classes, but a much higher proportion of students report good labs and a much lower proportion report bad laboratories than in public universities. A lower portion of students report that lecture is the predominant pedagogy. There is a much higher report of good teachers in private universities, though, as noted above, students may be more or less critical in different environments. On the face of it, private colleges have better resources.

However, the picture of the private university student is very different, and the private university experience serves a different purpose. A logistic regression predicting private university attendance portrays the following private school attendee (Table 6). Students who are more likely to attend a private university are older, graduated from a public high school, performed worse on their college entrance exams, live at home, and have parents who either have just elementary education or who attended college or higher. The crossover from private high school to public college and vice versa creates a policy conundrum, where students whose parents can afford private K-12 education are well-prepared for competitive and well-funded public universities, and students who attend public K-12 must resort to the leftover spots in higher education.

In general, public universities improve student scores more (figure 5): public schools improve by 14.1 points on average (and start higher); private schools improve by 12.7 (significant difference between both groups).

Fixed Effects, IV Estimates. In the full dataset and the matched sample, I find significant within- and between-institution variation in engineering student achievement.

In all of the models, between-institution variation is larger. However, it is notable that, for the subject-specific assessment, within- and between-institution variation is nearly equal, while between-institution variance is much larger than within-institution variance for the general knowledge test. Once students are selected into a university (general knowledge), there is less variation in how they utilize those resources (engineering knowledge).

In my instrumental variables estimate, I use location in a capital city, distance to college, a second-order term, school cost, and an interaction as instruments for three of the most public signals sent to students about university quality—whether a university is public or private, the ratio of PhDs on the faculty, and the proportion of the student body from high-income backgrounds. F-statistics for the first stage regressions (Table 7) are all greater than 10, and the coefficients for the excluded instruments are significant. I use an over-identification test to verify that these institutional factors are indeed endogenous to student achievement. I find that the instruments are valid, but they are only marginally statistically insignificant.

The variable I am most concerned about in terms of self-selection is the selection into a private university. However, I include two other potentially endogenous regressors—the ratio of PhDs on the faculty and the proportion of high income students in the student population. I am concerned not only about selection into private or public university, but also about selection into higher quality universities in both sectors. Both of these additional two variables would be noticeable indicators for students making their selection into university.

A comparison across the OLS/IV models seems to indicate I have removed some of the potential bias whereby students with higher ability would select into public universities. I also seem to have removed the bias whereby students would select into universities with a peer group with higher income. The most interesting result in comparing the OLS and IV models comes in looking at the removal of bias for the ratio of PhDs on the faculty; the omitted variable bias appears to move in opposite directions for the general versus the specific test. The doctor ratio variable appears to have been biased downward overall (students with lower achievement select into institutions with a higher ratio of PhDs). This may be because students with overall higher abilities may selected into institutions with a higher doctor ratio on faculty (as evidenced by the changed in the coefficients for the general test), but these students are not necessarily the ones who would then perform well as engineers. However, the factors that I instrument for are only the most visible of the factors that students might use to select their university, and I may not have been able to remove all of the omitted variable bias in the model. And, as the excluded instruments have low p-values in the overidentification test, I have reservations about the use of this model as my main source of results reported. In future work, I focus on the selection into private university as the primary endogenous variable of interest. Also, I separate out the OLS and FE results as the main results I discuss below.

Discussion and Implications

School matters. In every model, the additive effect of being a final-year as opposed to being a first-year was significant. This result seems obvious; of course students will know more about engineering at the end of a four year engineering program than at the beginning. The size of the change is notable though—an increase of approximately 0.5 standard deviations for the general test and nearly 1 standard deviation for the engineering-specific assessment. Of the school factors included in the model, teachers seem to matter the most; the largest result is the estimate of student reports of bad teachers, even controlling for varying private/public environments.

College does matter, but can it "make up for" discrepancies in pre-college factors? Effect sizes for school and home inputs were comparable, but the between-school variation was larger than within-institution variation across models. It should be noted that college dropout plagues the Brazilian system (Fava de Oliveira, 2011); the make-up of final years versus first years in this dataset is very different. It is differential. From first years to final years, the proportion of students in private universities goes down, the portion of students from higher income families or who attended private high schools goes up, and the portion of students whose parents did not go to college or who are black, mixed, or indigenous greatly decreases.

A student's identity is significantly related to staying in school and for how the student fares on the engineering assessment. A student's home background and pre-tertiary experiences also matter for school retention as well as for where they go to school and their achievement on the general assessment. As shown even in the models that control for previous achievement (the high school exit exam), the social and cultural resources that a student brings to college are important for navigating the university learning environment. This is true in particular for the creation of technological capital; a student's exposure to more resources in primary and secondary school prepares her to choose a tertiary engineering education experience and to make better use of the same learning resources.

University factors do matter, and policymakers would do well to invest in creating an effective school space for engineers. Effective teachers are at the heart of this puzzle, and more research is needed to understand what makes an effective teacher and how to train them. But, institutional resources can only do their job if students are prepared for university. As child development research has demonstrated the need for school readiness in young children, so this study begins to reveal that pre-college factors matter for university-level achievement. Private school high school graduates have much higher high school exit exams; well-prepared students from private high schools crossover to the public universities, and under-privileged students in the public high schools crossover to private universities.

As Brazil leads the way in data collection of this sort, it should continue to look to improve the information it gathers. I see from my rich amalgamated dataset that, across multiple sources of information, results are consistent. However, as I have information from both the student and institutional perspective, I also note that some information around the same constructs seems to be measuring different things. For example, the coefficients on “research emphasis” and “good labs” act in opposite directions. While the overall research environment of a university might be thriving, the laboratory facilities may not necessarily be conducive to undergraduate student learning.

A look at current Brazilian education practice could provide the inspiration for a policy change in higher education. Low-cost private schools (often coupled with public subsidies) may be one policy tool that could allow for policy intervention into the pre-university domain. The CENSO gives information on the financial situation of higher education institutions in Brazil. Unlike in the United States, the best-funded schools are the public schools. Comparing public to private schools (Table 14), one can see that the per-pupil amount spent solely on science/engineering equipment and the per-pupil income of the institutions are significantly larger. This is the case despite the small difference in the gain in scores from first year to final year in the two types of institutions.

Intervention to support the development of faculty within the private universities may also serve to raise the achievement of the students who are tracked into this part of the system. Perhaps even more promising, though, is the expansion and support of high-quality public higher education. Following on McCowan (2007)'s recommendations, interventions and incentives that build on the success of public higher education and expand access to its opportunities—through distance education, for example—could lead to both increased quality and equity.

The formal school career of engineers is fraught with choices and challenges. Even after the high-stakes selection process that is a barrier to getting into university engineering programs, this more-homogenous group of students sees differential attrition, differential achievement, and, anecdotally, differential job success. Of course the students who do get through to the final year of an engineering program are higher performing, but which students are these? Are they prepared enough? And, what investments helped them get there?

A major policy recommendation I suggest based on these data is to provide a set of incentives specifically for the students most at-risk for stop-out during the college experience: low-income and minority students. There is clearly a systematic pattern of differential stopout for engineers who come into the higher education system with less technological capital already at their disposal. Providing tailored, targeted support for these students to excel in their coursework, to complete their degrees, and to enter the engineering workforce would mitigate the exit of a substantial number of potential engineers from the engineering pipeline.

The nature of engineering training may necessitate another policy recommendation—a closer connection between industry and formal schooling and between tertiary engineering education and out-of-school factors. The creation of technological capital begins in the home, and engineering college programs might see more success in their students if student preparation began earlier. The same is true for companies preparing Brazil's next generation of engineers—the preparation of quality engineering workers begins before their first day on the job.

What does it mean to invest in one's own engineering education? The large private sector in higher education cannot be ignored in engineering training. Does it change the way one perceives the quality of the resources at hand? On average, students in private universities perform worse, though the student perspective on resources if significantly better. Take teacher quality, for example. The average "good teacher" rating is significantly higher in private than in public universities. This is the case despite the fact that the proportion of doctors on the faculty in public universities is nearly three times higher. It may be the case that students rate the quality of a significant investment on their part as higher than if they were not paying for it. However, the learning environment in private universities may also be more conducive to a nurturing experience; for example, the amount of group work reported in private universities is significantly higher. Given the preparation of the students they receive, private universities may, overall, be providing an effective learning experience.

Future work will include analysis of restricted data for 2008 as well as more detailed analysis of university resources. In 2011, engineering students were again sampled, and they will be included in follow-up work as well. Brazil has taken the lead in gathering university-level assessment data. It now has the opportunity to take the lead in solving problems of educational quality and equity that continue to perplex policymakers worldwide.

Figures and Tables

Table 1. *OLS Prediction of Scores with Full ENADE Engineers Set (2005/2008)*

	Full score	General	Engineering
Sex	-0.06 (0.30)	2.14 (0.40)	-0.79 (0.29)
Age	-0.01 (0.03)	-0.03 (0.03)	0.00 (0.03)
Black	-1.95 (0.31)	-1.40 (0.41)	-2.13 (0.33)
Mixed	-1.29 (0.30)	-0.43 (0.42)	-1.57 (0.30)
Asian	-0.18 (0.52)	-0.65 (0.64)	-0.02 (0.56)
Indigenous	-2.10 (0.74)	-1.95 (0.93)	-2.15 (0.80)
Private	0.65 (0.22)	0.59 (0.32)	0.67 (0.23)
Computing	1.17 (0.20)	1.46 (0.24)	1.07 (0.21)
Study	0.36 (0.04)	0.42 (0.04)	0.34 (0.04)
Parent ed: elementary	2.72 (0.82)	4.16 (1.33)	2.24 (0.79)
Parent ed: junior secondary	2.35 (0.84)	3.67 (1.30)	1.91 (0.82)
Parent ed: senior secondary	2.50 (0.85)	3.77 (1.31)	2.07 (0.82)
Parent ed: higher education	3.91 (0.88)	4.82 (1.34)	3.61 (0.84)
Family income low	-0.26 (0.27)	0.78 (0.33)	-0.60 (0.28)
Family income high	0.14 (0.23)	1.09 (0.30)	-0.18 (0.24)
“Good” teachers	-7.33 (3.88)	-5.44 (4.31)	-7.96 (3.96)
“Bad” teachers	-71.85 (12.70)	-61.55 (13.69)	-75.29 (12.88)
“Good” labs	-9.42 (4.43)	-8.59 (4.34)	-9.70 (4.61)
“Bad” labs	11.59 (9.01)	9.96 (9.04)	12.14 (9.34)
Medium class size	-2.12 (3.52)	-0.66 (3.25)	-2.61 (3.76)
Large class size	-8.85 (3.59)	-5.69 (3.67)	-9.91 (3.86)
Year of exam	-0.69 (0.11)	-1.09 (0.14)	-0.56 (0.11)
First year	-6.72 (0.28)	-3.99 (0.32)	-7.64 (0.31)
Constant	1433.27 (224.69)	2249.57 (283.65)	1163.84 (227.15)
Observations	125160	125161	125160
R-squared	0.14	0.05	0.14
Adjusted R-squared			
F	57.85	35.50	57.63
D.f. model	23	23	23
D.r. residuals	400	400	400

Standard errors in parentheses
Note: OLS model uses student weights.

Table 2. *Fixed effects by institution (2005/2008)*

	Full score	General	Engineering
Sex	-0.07 (0.14)	2.33 (0.20)	-0.86 (0.15)
Age	0.08 (0.01)	0.04 (0.02)	0.09 (0.01)
Black	-1.47 (0.24)	-1.11 (0.35)	-1.60 (0.26)
Mixed	-0.54 (0.15)	0.08 (0.23)	-0.75 (0.17)
Asian	-0.62 (0.34)	-1.05 (0.50)	-0.48 (0.36)
Indigenous	-1.34 (0.59)	-1.41 (0.86)	-1.31 (0.63)
Private	0.32 (0.12)	0.40 (0.17)	0.29 (0.13)
Computing	1.27 (0.12)	1.39 (0.17)	1.24 (0.12)
Study	0.18 (0.02)	0.25 (0.03)	0.16 (0.02)
Parent ed: elementary	2.35 (0.72)	3.45 (1.05)	1.98 (0.77)
Parent ed: junior sec.	1.99 (0.72)	3.09 (1.05)	1.63 (0.77)
Parent ed: senior sec.	1.96 (0.71)	2.95 (1.04)	1.63 (0.76)
Parent ed: higher ed.	2.58 (0.71)	3.33 (1.04)	2.33 (0.76)
Family income low	-0.99 (0.13)	0.24 (0.19)	-1.40 (0.14)
Family income high	0.74 (0.16)	1.42 (0.23)	0.51 (0.17)
Year of exam	-0.46 (0.05)	-1.00 (0.08)	-0.28 (0.06)
First year	-5.55 (0.12)	-3.32 (0.17)	-6.29 (0.13)
Constant	955.69 (103.44)	2060.99 (151.48)	589.82 (111.09)
Observations	48913	48914	48913
R-squared	0.07	0.02	0.08
Adjusted R-squared	0.07	0.01	0.07
F	225.76	66.61	248.64
D.f. model	406	406	406
D.r. residuals	48506	48507	48506

Standard errors in parentheses
Fixed effect by institution.

Table 3. *Cohort Comparisons (2005/2008)*

Full scores			
	2005/2008 cohort	2008 first to final	2005 first to final
(Mean) first year scores	0.36 (0.03)		0.44 (0.02)
(Mean) first year scores		0.48 (0.03)	
(Mean) sex	-6.16 (1.65)	1.36 (1.63)	-6.25 (1.40)
(Mean) age	-0.44 (0.16)	-0.38 (0.16)	0.40 (0.14)
(Mean) black	-1.17 (5.64)	-9.03 (5.07)	-11.07 (4.72)
(Mean) mixed	-10.31 (2.74)	-5.57 (2.79)	-7.92 (2.26)
(Mean) asian	-5.97 (9.40)	-15.94 (10.16)	-10.37 (7.48)
(Mean) indigenous	-7.80 (18.52)	-29.03 (18.75)	3.06 (9.97)
(Mean) private pre-college	-2.04 (2.25)	-3.14 (2.22)	1.34 (1.80)
(Mean) computing	-5.33 (2.29)	-1.87 (2.26)	5.65 (1.87)
(Mean) study	1.29 (0.37)	1.12 (0.34)	1.69 (0.28)
(Mean) parent ed: elem	16.07 (11.49)	7.86 (9.76)	-18.14 (10.19)
(Mean) parent ed: junior secondary	17.09 (11.25)	12.89 (9.52)	-11.11 (10.00)
(Mean) parent ed: senior secondary	18.02 (10.90)	14.73 (9.02)	-14.13 (9.72)
(Mean) parent ed: higher education	21.65 (10.91)	16.06 (9.06)	-11.05 (9.74)
(Mean) family income low	-1.91 (2.04)	-3.26 (2.01)	0.14 (1.81)
(Mean) family income high	-8.42 (3.86)	-3.46 (3.87)	-10.24 (3.00)
(Mean) “good” teachers	2.34 (3.53)	4.65 (3.54)	-10.07 (3.17)
(Mean) “bad” teachers	-7.18 (10.87)	4.59 (10.21)	-25.05 (9.51)
(Mean) “good” labs	-3.47 (3.30)	-2.53 (3.36)	-2.51 (2.90)
(Mean) “bad” labs	-3.58 (6.37)	-10.09 (6.14)	-1.44 (5.83)
(Mean) medium average class size	-2.21 (2.91)	-3.33 (3.01)	-1.43 (2.36)
(Mean) large average class size	-5.31 (2.94)	-7.32 (3.00)	-4.49 (2.80)
Constant	26.37 (12.26)	25.31 (10.51)	32.91 (10.78)
Observations	894	948	873
R-squared	0.43	0.42	0.51
Adjusted R-squared	0.42	0.40	0.50
F	29.82	29.95	40.97
D.f. model	22	22	22
D.r. residuals	871	925	850
Standard errors in parentheses			
Institution-level cohort predictions			

Table 4. *OLS and IV Models for Matched Data*

	OLS Model Predicting full	IV Model Predicting full	OLS Model Predicting general	IV Model Predicting general	OLS Model Predicting subject	IV Model Predicting subject
Doctor ratio	0.51	2.33	0.39	-0.36	0.47	3.34
	(0.04)	(0.75)	(0.05)	(0.72)	(0.04)	(0.89)
Average high income	0.12	-0.82	0.16	0.37	0.08	-1.29
	(0.04)	(0.39)	(0.05)	(0.37)	(0.04)	(0.47)
Private university	-0.15	-0.01	-0.07	-0.43	-0.15	0.18
	(0.02)	(0.28)	(0.02)	(0.27)	(0.02)	(0.34)
Sex	0.01	0.02	0.14	0.11	-0.04	-0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age	-0.01	-0.01	-0.00	0.00	-0.01	-0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Black	-0.08	-0.06	-0.02	-0.03	-0.09	-0.07
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Mixed	-0.01	0.00	0.02	0.02	-0.02	-0.01
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Asian	-0.04	-0.05	-0.04	-0.04	-0.03	-0.05
	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)
Indigenous	-0.01	0.00	0.01	0.04	-0.02	-0.02
	(0.06)	(0.06)	(0.07)	(0.05)	(0.06)	(0.08)
Private pre-college	-0.04	-0.02	-0.02	-0.00	-0.04	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Computing	-0.00	0.01	0.01	0.00	-0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Study	0.02	0.01	0.02	0.02	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
English	0.07	0.07	0.10	0.09	0.04	0.06
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ENEM objective	0.01	0.00	0.01	0.00	0.01	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ENEM redactive	-0.00	0.00	0.00	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Live with family	-0.01	0.01	-0.01	0.02	-0.01	0.01
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Parental ed: elementary	0.15	0.20	0.12	0.17	0.14	0.19
	(0.09)	(0.07)	(0.14)	(0.09)	(0.08)	(0.08)
Parental ed: junior sec.	0.11	0.13	0.12	0.13	0.09	0.11
	(0.11)	(0.08)	(0.14)	(0.08)	(0.09)	(0.10)

Parental ed: senior sec.	0.09 (0.10)	0.14 (0.08)	0.11 (0.13)	0.15 (0.09)	0.07 (0.09)	0.12 (0.09)
Parental ed: higher ed.	0.09 (0.10)	0.16 (0.08)	0.12 (0.14)	0.14 (0.09)	0.07 (0.09)	0.15 (0.09)
Family income: lower-mid.	-0.02 (0.02)	-0.03 (0.03)	-0.02 (0.02)	-0.03 (0.03)	-0.01 (0.02)	-0.03 (0.03)
Family income: middle income	-0.02 (0.02)	-0.03 (0.02)	-0.03 (0.02)	-0.02 (0.03)	-0.01 (0.02)	-0.03 (0.02)
Family income: higher mid.	-0.01 (0.02)	-0.03 (0.03)	-0.05 (0.03)	-0.05 (0.03)	0.00 (0.02)	-0.02 (0.03)
Family income: high	0.04 (0.03)	0.04 (0.03)	-0.03 (0.04)	-0.04 (0.04)	0.06 (0.03)	0.08 (0.03)
Family income: highest	0.08 (0.03)	0.13 (0.04)	-0.07 (0.04)	-0.07 (0.05)	0.12 (0.03)	0.21 (0.05)
Family income: none	-0.02 (0.08)	-0.00 (0.08)	-0.12 (0.08)	-0.03 (0.08)	0.02 (0.08)	0.01 (0.09)
Average “good” teacher rating	0.08 (0.05)	0.39 (0.10)	0.07 (0.06)	0.04 (0.09)	0.07 (0.06)	0.52 (0.11)
Average “bad” teacher rating	-1.11 (0.15)	-0.85 (0.27)	-0.67 (0.16)	-0.77 (0.26)	-1.09 (0.15)	-0.80 (0.32)
IP (number of patents)	0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)
Research emphasis	0.01 (0.02)	-0.11 (0.03)	0.00 (0.02)	0.02 (0.03)	0.01 (0.02)	-0.16 (0.04)
Average “good” lab rating	-0.09 (0.04)	0.70 (0.22)	-0.14 (0.05)	0.02 (0.21)	-0.06 (0.04)	0.94 (0.26)
Average “bad” lab rating	-0.23 (0.08)	1.26 (0.49)	-0.17 (0.09)	-0.48 (0.47)	-0.22 (0.08)	1.94 (0.58)

Average female prop.	0.38 (0.05)	0.03 (0.11)	0.10 (0.05)	0.09 (0.10)	0.42 (0.05)	0.00 (0.13)
Average black prop.	0.66 (0.13)	0.24 (0.17)	0.75 (0.14)	0.45 (0.12)	0.51 (0.13)	0.26 (0.14)
Average mixed prop.	-0.23 (0.05)	-1.22 (0.40)	-0.03 (0.06)	-0.07 (0.17)	-0.27 (0.05)	0.35 (0.21)
Average asian prop.	-0.40 (0.14)	-0.89 (0.30)	-0.40 (0.15)	0.12 (0.37)	-0.33 (0.14)	-1.72 (0.47)
Average indigenous prop.	-0.30 (0.27)	0.03 (0.11)	0.36 (0.29)	0.22 (0.29)	-0.51 (0.27)	-1.31 (0.36)
Lectures	0.61 (0.06)	-0.35 (0.24)	0.33 (0.07)	0.31 (0.23)	0.62 (0.06)	-0.62 (0.28)
Group work	-0.10 (0.09)	-0.10 (0.08)	-0.18 (0.09)	-0.04 (0.08)	-0.05 (0.09)	-0.12 (0.10)
Seminars	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Incoming	-0.75 (0.01)	-0.57 (0.02)	-0.31 (0.02)	-0.21 (0.02)	-0.79 (0.01)	-0.68 (0.02)
Constant	-0.04 (0.14)	-0.64 (0.31)	-0.70 (0.19)	-0.05 (0.30)	0.23 (0.13)	-0.84 (0.36)
Observations	31033	27499	31033	27499	31033	27499
R^2	0.31	0.17	0.16	0.13	0.29	0.06
Adjusted R^2	0.31	0.17	0.15	0.13	0.29	0.06
F	275.00	233.49	111.68	114.33	249.14	192.00
D.f. model	51	41	51	41	51	41
Sarganp		0.12		0.18		0.15
Archi2p		0.00		0.05		0.00

Table 5. *Prediction of Student Being in Private University*

	(1) Logit Model Predicting that student is in a private univ.	(2) Logit Model Predicting a student's enrollment in a private univ. (just student chars.)
Private univ.		
Sex	-0.02	-0.31
	(0.09)	(0.03)
Age	0.05	-0.02
	(0.01)	(0.00)
Black	-0.07	0.10
	(0.21)	(0.07)
Mixed	-0.06	-0.22
	(0.10)	(0.04)
Asian	-0.04	-0.08
	(0.21)	(0.09)
Indigenous	0.17	0.07
	(0.45)	(0.13)
Private pre-college	-0.23	-0.39
	(0.09)	(0.04)
Computing	0.02	0.40
	(0.08)	(0.03)
Study	-0.03	-0.14
	(0.01)	(0.01)
English	-0.02	-0.25
	(0.07)	(0.03)
ENEM objective	-0.00	-0.02
	(0.00)	(0.00)
ENEM redactive	-0.00	0.00
	(0.00)	(0.00)
Live with family	0.32	0.26
	(0.15)	(0.07)
Parental ed: elementary	0.66 (0.84)	-0.31 (0.31)
Parental ed: junior sec.	0.87 (0.92)	-0.19 (0.30)
Parental ed: senior sec.	0.80 (0.89)	-0.31 (0.32)
Parental ed: higher	0.85	-0.46

ed.	(0.88)	(0.34)
Family income: lower-mid.	-0.18 (0.15)	0.29 (0.05)
Family income: middle income	-0.10 (0.17)	0.28 (0.05)
Family income: higher mid.	0.02 (0.16)	0.34 (0.05)
Family income: high	0.28 (0.23)	0.62 (0.07)
Family income: highest	0.38 (0.31)	0.99 (0.08)
Family income: none	-0.81 (0.45)	0.16 (0.17)
Average “good” teacher rating	3.57 (0.41)	
Average “bad” teacher rating	-13.45 (1.06)	
IP (number of patents)	0.00 (0.00)	
Doctor ratio	-12.78 (0.39)	
Research emphasis	0.22 (0.14)	
Average “good” lab rating	2.56 (0.27)	
Average “bad” lab rating	-0.76 (0.53)	
Average class size: medium	-2.77 (0.21)	
Average class size: large	2.38 (0.27)	
Overall STR	0.09 (0.01)	
Overall gender ratio	0.36 (0.05)	
Scholarships	66.32 (2.84)	

Library area	-0.00	
	(0.00)	
Laboratory area	0.00	
	(0.00)	
Computers	-0.00	
	(0.00)	
Average female prop.	-4.12	
	(0.33)	
Average low income prop.	1.27	
	(0.52)	
Average high education prop.	-1.14	
	(0.74)	
Average black prop.	-0.68	
	(0.72)	
Average mixed prop.	0.70	
	(0.34)	
Average asian prop.	18.19	
	(1.17)	
Average indigenous prop.	-7.32	
	(2.20)	
Average high educaiton	1.33	
	(0.44)	
Lectures	-2.38	
	(0.48)	
Group work	3.57	
	(0.72)	
Practical work	6.99	
	(1.20)	
Seminars	0.01	
	(0.00)	
Constant	-0.15	2.35
	(1.22)	(0.40)
Observations	31060	31060

Table 6. *Institutional Fixed Effects for All Universities, Private, and Public by Full, General, and Specific Assessment*

	(1) FE Model Predicting full (all univs.)	(2) FE Model Predicting full (private univs.)	(3) FE Model Predicting full (public univs.)	(4) FE Model Predicting general (all univs.)	(5) FE Model Predicting general (private univs.)	(6) FE Model Predicting general (public univs.)	(7) FE Model Predicting subject (all univs.)	(8) FE Model Predicting subject (private univs.)	(9) FE Model Predicting subject (public univs.)
Sex	0.00	0.06	-0.06	0.14	0.18	0.10	-0.05	0.01	-0.11
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Age	-0.01	0.00	-0.04	-0.00	0.01	-0.03	-0.01	0.00	-0.03
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Black	-0.08	-0.03	-0.16	-0.03	0.01	-0.06	-0.09	-0.04	-0.17
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.05)	(0.03)	(0.03)	(0.04)
Mixed	-0.01	0.01	-0.03	0.02	0.06	-0.01	-0.02	-0.01	-0.03
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
Asian	-0.04	-0.05	-0.05	-0.04	0.01	-0.08	-0.04	-0.06	-0.02
	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)	(0.03)	(0.04)	(0.05)
Indigenous	-0.03	0.04	-0.11	0.00	0.09	-0.08	-0.04	0.02	-0.11
	(0.05)	(0.07)	(0.09)	(0.07)	(0.09)	(0.10)	(0.05)	(0.06)	(0.09)
Private pre-college	-0.04	0.00	-0.08	-0.02	-0.01	-0.04	-0.04	0.01	-0.08
	(0.01)	(0.02)	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)
Computing	0.00	-0.01	0.02	0.01	0.00	0.02	-0.00	-0.01	0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Study	0.01	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
English	0.06	0.07	0.04	0.09	0.12	0.05	0.04	0.04	0.03
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
ENEM objective	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

ENEM redactive	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Live with family	0.00 (0.02)	0.02 (0.03)	-0.02 (0.03)	-0.00 (0.03)	0.02 (0.04)	-0.02 (0.03)	0.00 (0.02)	0.02 (0.03)	-0.01 (0.03)
Parental ed: elementary	0.14 (0.11)	0.15 (0.10)	0.11 (0.17)	0.10 (0.15)	0.18 (0.17)	-0.05 (0.15)	0.13 (0.09)	0.11 (0.08)	0.15 (0.18)
Parental ed: junior sec.	0.12 (0.12)	0.16 (0.10)	0.08 (0.19)	0.12 (0.15)	0.23 (0.18)	-0.05 (0.14)	0.10 (0.10)	0.11 (0.09)	0.11 (0.19)
Parental ed: senior sec.	0.11 (0.11)	0.12 (0.10)	0.09 (0.17)	0.11 (0.14)	0.21 (0.18)	-0.04 (0.13)	0.09 (0.10)	0.07 (0.09)	0.13 (0.18)
Parental ed: higher ed.	0.10 (0.11)	0.14 (0.10)	0.07 (0.18)	0.11 (0.14)	0.21 (0.18)	-0.05 (0.13)	0.08 (0.10)	0.09 (0.09)	0.10 (0.19)
Family income: lower-mid.	-0.02 (0.02)	-0.04 (0.03)	-0.00 (0.03)	-0.03 (0.02)	-0.03 (0.03)	-0.01 (0.05)	-0.02 (0.02)	-0.03 (0.02)	0.00 (0.03)
Family income: middle income	-0.02 (0.02)	-0.03 (0.02)	0.00 (0.03)	-0.02 (0.02)	-0.02 (0.03)	-0.03 (0.05)	-0.01 (0.02)	-0.03 (0.02)	0.01 (0.03)
Family income: higher mid.	-0.01 (0.02)	-0.05 (0.03)	0.03 (0.03)	-0.04 (0.03)	-0.07 (0.03)	-0.01 (0.05)	0.00 (0.02)	-0.03 (0.03)	0.05 (0.03)
Family income: high	0.03 (0.03)	-0.01 (0.04)	0.06 (0.04)	-0.02 (0.03)	-0.06 (0.04)	0.01 (0.06)	0.04 (0.03)	0.01 (0.04)	0.07 (0.04)
Family income: highest	0.05 (0.03)	-0.02 (0.04)	0.15 (0.05)	-0.06 (0.04)	-0.11 (0.05)	0.01 (0.06)	0.09 (0.03)	0.02 (0.04)	0.17 (0.05)
Family income:	-0.01 (0.08)	-0.03 (0.09)	0.03 (0.11)	-0.09 (0.08)	-0.09 (0.11)	-0.07 (0.13)	0.03 (0.08)	-0.00 (0.09)	0.07 (0.11)

none									
Overall STR	-0.01	-0.00	-0.16	-0.01	-0.00	-0.04	-0.00	-0.00	-0.18
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
Overall gender ratio	0.04	0.03	0.04	0.04	0.01	0.05	0.04	0.04	0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Incoming	-0.73	-0.59	-0.90	-0.28	-0.33	-0.30	-0.78	-0.59	-0.98
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Constant	0.25	-0.50	1.51	-0.38	-1.02	0.82	0.45	-0.21	1.52
	(0.13)	(0.13)	(0.21)	(0.17)	(0.20)	(0.19)	(0.12)	(0.13)	(0.22)
Observations	31060	16288	14772	31060	16288	14772	31060	16288	14772
R^2	0.15	0.14	0.19	0.06	0.09	0.04	0.15	0.12	0.20
Adjusted R^2	0.14	0.13	0.18	0.05	0.07	0.04	0.14	0.10	0.20
F	213.67	100.29	129.94	75.66	58.80	26.09	208.59	81.76	143.08
D.f. model	333	247	111	333	247	111	333	247	111
D.r. residuals	30726	16040	14660	30726	16040	14660	30726	16040	14660
Within-institution variance explained	0.15	0.14	0.19	0.06	0.09	0.04	0.15	0.12	0.20
Between-institution variance explained	0.28	0.15	0.10	0.35	0.23	0.11	0.21	0.09	0.10
Overall variance explained	0.22	0.18	0.15	0.11	0.11	0.06	0.20	0.15	0.16

Table 7. *First Stage Regressions Predicting Instrumented Variables*

	(1) First-stage: private univ.	(2) First-stage: average high income	(3) First-stage: doctor ratio
Sex	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Age	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Black	-0.00	0.01	0.00
	(0.01)	(0.00)	(0.00)
Mixed	0.00	0.01	-0.00
	(0.00)	(0.00)	(0.00)
Asian	0.00	-0.00	-0.00
	(0.01)	(0.00)	(0.00)
Indigenous	-0.03	0.01	0.00
	(0.02)	(0.01)	(0.01)
Private	-0.02	0.01	0.01
	(0.00)	(0.00)	(0.00)
Computing	0.02	-0.00	-0.01
	(0.00)	(0.00)	(0.00)
Study	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
English	-0.01	0.01	0.01
	(0.00)	(0.00)	(0.00)
ENEM objective	-0.03	0.01	0.02
	(0.00)	(0.00)	(0.00)
ENEM redactive	0.01	-0.00	-0.01
	(0.00)	(0.00)	(0.00)
Live with family	0.03	0.00	-0.01
	(0.01)	(0.00)	(0.00)
Parental ed: elementary	-0.02	-0.01	0.01
	(0.02)	(0.01)	(0.01)

Parental ed: junior sec.	-0.00 (0.02)	-0.01 (0.01)	0.00 (0.01)
Parental ed: senior sec.	-0.01 (0.02)	-0.00 (0.01)	0.00 (0.01)
Parental ed: higher ed.	-0.01 (0.02)	0.01 (0.01)	0.01 (0.01)
Family income: lower-mid.	0.00 (0.01)	-0.01 (0.00)	-0.00 (0.00)
Family income: middle income	0.00 (0.01)	-0.01 (0.00)	0.00 (0.00)
Family income: higher mid.	0.00 (0.01)	0.01 (0.00)	0.00 (0.00)
Family income: high	0.02 (0.01)	0.03 (0.00)	-0.00 (0.00)
Family income: highest	0.04 (0.01)	0.06 (0.00)	-0.01 (0.01)
Family income: none	0.00 (0.02)	-0.01 (0.01)	0.01 (0.01)
Lectures	-1.03 (0.02)	0.22 (0.01)	0.74 (0.01)
Group work	0.11 (0.03)	-0.14 (0.01)	-0.08 (0.01)
Seminars	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
“Good” labs	0.96 (0.01)	0.05 (0.00)	-0.29 (0.01)
“Bad” labs	0.47 (0.02)	0.04 (0.01)	-0.67 (0.01)
Incoming	0.01 (0.00)	-0.01 (0.00)	0.00 (0.00)
Average female	-0.64 (0.01)	0.05 (0.00)	0.32 (0.01)

Average black	0.04	-0.25	-0.03
	(0.04)	(0.01)	(0.02)
Average mix	-0.19	-0.09	-0.15
	(0.01)	(0.00)	(0.01)
Average asian	0.45	0.21	0.48
	(0.04)	(0.01)	(0.02)
Average indigenous	0.69	-0.61	-0.26
	(0.08)	(0.03)	(0.04)
Research emphasis	-0.04	-0.03	0.06
	(0.00)	(0.00)	(0.00)
Ip	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
“Good” teachers	0.35	0.17	-0.14
	(0.02)	(0.01)	(0.01)
“Bad” teachers	-0.70	-0.17	-0.21
	(0.04)	(0.01)	(0.02)
Distance	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)
Distance tuition	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)
Distance^2	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)
Capital city	0.03	0.05	0.01
	(0.00)	(0.00)	(0.00)
Per-pupil tuition	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)
Constant	0.43	-0.04	0.12
	(0.03)	(0.01)	(0.02)
Observations	31060	31060	31060
R^2	0.73	0.48	0.68
F	1950.00	651.78	1493.73

Table 8. *Comparison of Demographics of Engineers/Non-Engineers*

	Non-engineers			Sampled engineers		
Variable	Obs	M	SD	Obs	M	SD
White	5256980	0.57	0.49	30267	0.71	0.45
Mixed	5256980	0.31	0.46	30267	0.20	0.40
Black	5256980	0.06	0.24	30267	0.03	0.18
Asian	5256980	0.05	0.22	30267	0.05	0.21
Indigenous	5256980	0.01	0.09	30267	0.00	0.07
Single	5277133	0.93	0.26	30308	0.99	0.11
Married	5277133	0.06	0.24	30308	0.01	0.10
Separated	5277133	0.01	0.09	30308	0.00	0.03
Widow	5277133	0.00	0.03	30308	0.00	0.02
Father ed: no school	5262671	0.06	0.25	30262	0.01	0.10
Father ed: early primary	5262671	0.29	0.45	30262	0.12	0.33
Father ed: primary	5262671	0.15	0.36	30262	0.11	0.31
Father ed: junior secondary	5262671	0.06	0.24	30262	0.06	0.24
Father ed: senior secondary	5262671	0.16	0.37	30262	0.23	0.42
Father ed: some higher education	5262671	0.04	0.20	30262	0.09	0.28
Father ed: undergraduate degree	5262671	0.12	0.33	30262	0.27	0.44
Father ed: postgraduate	5262671	0.04	0.19	30262	0.09	0.28
Mother ed: no school	5276866	0.06	0.23	30302	0.01	0.10
Mother ed: early primary	5276866	0.28	0.45	30302	0.11	0.31
Mother ed: primary	5276866	0.17	0.38	30302	0.11	0.31
Mother ed: junior secondary	5276866	0.07	0.25	30302	0.06	0.24
Mother ed: senior secondary	5276866	0.19	0.40	30302	0.27	0.44
Mother ed: some higher	5276866	0.05	0.21	30302	0.08	0.27

education						
Mother ed: undergraduate degree	5276866	0.12	0.33	30302	0.27	0.44
Mother ed: postgraduate	5276866	0.04	0.19	30302	0.09	0.28
Lower middle income	5243137	0.31	0.46	30134	0.22	0.41
Middle income	5243137	0.19	0.39	30134	0.28	0.45
Higher middle income	5243137	0.14	0.35	30134	0.31	0.46
High income	5243137	0.03	0.18	30134	0.07	0.26
Max income	5243137	0.02	0.13	30134	0.03	0.18
No income	5243137	0.01	0.11	30134	0.01	0.08
No computers	5123229	0.32	0.47	30125	0.18	0.38
One computer	5123229	0.28	0.45	30125	0.54	0.50
Two computers	5123229	0.03	0.18	30125	0.08	0.27
Three or more computers	5123229	0.01	0.09	30125	0.02	0.14
Secondary only public	5259275	0.68	0.47	30289	0.40	0.49
Secondary some private	5259275	0.05	0.22	30289	0.06	0.24
Secondary only private	5259275	0.25	0.44	30289	0.52	0.50
Secondary teachers excellent	5271361	0.00	0.03	30271	0.00	0.04

Table 9. *Physical Infrastructure (Student and Institutional Perspective)*

	"Good" labs	"Bad" labs	Lab area	Library area	Computers	Funding
"Good" labs	1.00					
"Bad" labs	-0.81 (0.00)	1.00				
Lab area	-0.18 (0.00)	0.23 (0.00)	1.00			
Library area	-0.15 (0.00)	0.21 (0.00)	0.79 (0.00)	1.00		
Computers	-0.16 (0.00)	-0.00 (0.07)	-0.09 (0.00)	-0.09 (0.00)	1.00	
Funding	-0.12 (0.00)	0.08 (0.00)	-0.00 (0.26)	-0.03 (0.00)	0.12 (0.00)	1.00

Table 10. *Teacher Quality (Student and Institutional Perspective)*

	"Good" profs	"Bad" profs	Doctor ratio	Lecture ave	Group work ave	Practical work ave	Seminars
"Good" profs	1.00						
"Bad" profs	-0.54 (0.00)	1.00					
Doctor ratio	-0.36 (0.00)	0.11 (0.00)	1.00				
Lecture ave	-0.44 (0.00)	0.14 (0.00)	0.72 (0.00)	1.00			
Group work ave	0.14 (0.00)	0.08 (0.00)	-0.45 (0.00)	-0.59 (0.00)	1.00		
Practical work ave	0.30 (0.00)	-0.15 (0.00)	-0.41 (0.00)	-0.56 (0.00)	0.14 (0.00)	1.00	
Seminars	0.04 (0.00)	-0.03 (0.00)	0.00 (0.04)	0.03 (0.00)	-0.00 (0.17)	0.10 (0.00)	1.00

Table 11. *Learning Environment: Class Size (Student and Institutional Perspective)*

	"Medium" class ave	"Large" class ave	Student/ faculty ratio
"Medium" class ave	1.00		
"Large" class ave	-0.57 (0.00)	1.00	
Student/ faculty ratio	-0.10 (0.00)	0.17 (0.00	1.00

Table 12. *Learning Environment: Peer Composition (Student and Institutional Perspective)*

	Average low income	Average high income
Scholarships	0.04 (0.00)	0.01 (0.06)
	Institutional gender ratio	
Sample average female	0.29 (0.00)	

Table 13. *Private/Public University Students, Incoming/Outgoing Students*

	Public						Private					
	Final year			First year			Final year			First year		
	Obs	M	SD	Obs	M	SD	Obs	M	SD	Obs	M	SD
Gender	4150	0.31	0.46	12325	0.29	0.45	3759	0.26	0.44	14404	0.21	0.41
Age	4150	23.53	1.63	12325	20.56	2.06	3759	23.76	2.17	14404	20.88	2.90
Black	2715	0.02	0.15	7087	0.04	0.20	2978	0.02	0.13	9489	0.05	0.23
Mixed	2715	0.17	0.37	7087	0.20	0.40	2978	0.11	0.32	9489	0.18	0.38
Asian	2715	0.05	0.22	7087	0.04	0.19	2978	0.06	0.23	9489	0.03	0.18
Indigenous	2715	0.01	0.09	7087	0.01	0.09	2978	0.00	0.06	9489	0.01	0.10
Private	2712	0.67	0.47	7099	0.62	0.48	2979	0.66	0.48	9471	0.45	0.50
Computing	2709	0.56	0.50	6995	0.30	0.46	2971	0.62	0.48	9375	0.38	0.49
Study	2701	5.15	3.24	7073	4.94	3.25	2970	3.59	2.85	9438	3.68	2.86
English	2713	0.74	0.44	7095	0.56	0.50	2978	0.69	0.46	9469	0.47	0.50
ENEM objective	4150	0.22	1.07	12325	0.28	0.97	3759	-0.24	1.01	14404	-0.24	0.93
ENEM redactive	4150	0.09	1.05	12325	0.13	1.01	3759	-0.15	1.00	14404	-0.10	0.95

Live with family	3715	0.93	0.25	10969	0.94	0.24	3302	0.96	0.20	12402	0.95	0.21
Parental ed: elementary	2696	0.05	0.21	7056	0.05	0.21	2963	0.05	0.22	9437	0.09	0.28
Parental ed: junior secondary	2696	0.06	0.23	7056	0.06	0.25	2963	0.06	0.24	9437	0.11	0.32
Parental ed: senior secondary	2696	0.26	0.44	7056	0.31	0.46	2963	0.27	0.44	9437	0.35	0.48
Parental ed: higher education	2696	0.63	0.48	7056	0.58	0.49	2963	0.62	0.49	9437	0.44	0.50
Lower middle income	3699	0.11	0.32	10891	0.23	0.42	3286	0.08	0.28	12309	0.27	0.44
Middle income	3699	0.25	0.43	10891	0.29	0.45	3286	0.22	0.41	12309	0.30	0.46
Higher middle income	3699	0.39	0.49	10891	0.31	0.46	3286	0.43	0.49	12309	0.25	0.44
Higher income	3699	0.12	0.33	10891	0.06	0.23	3286	0.14	0.34	12309	0.05	0.22
Max income	3699	0.06	0.24	10891	0.02	0.14	3286	0.09	0.29	12309	0.03	0.16
No income	3699	0.01	0.09	10891	0.01	0.08	3286	0.01	0.07	12309	0.01	0.07
"Good"	4150	0.24	0.07	12325	0.23	0.09	3755	0.41	0.12	14378	0.41	0.14

teachers												
"Bad" teachers	4150	0.07	0.05	12325	0.07	0.05	3755	0.03	0.03	14378	0.03	0.04
Ip	4150	795.03	3650.71	12325	568.05	3071.99	3759	5.44	161.86	14404	105.66	766.83
Doctor ratio	4150	0.53	0.21	12325	0.49	0.22	3759	0.21	0.10	14404	0.17	0.10
Research emphasis	2600	0.85	0.36	7829	0.78	0.42	2506	0.47	0.50	8342	0.62	0.49
"Good" labs	4150	0.29	0.15	12325	0.29	0.19	3755	0.74	0.16	14378	0.72	0.18
"Bad" labs	4150	0.18	0.11	12325	0.19	0.12	3755	0.04	0.07	14378	0.05	0.08
Medium class size	4150	0.59	0.14	12325	0.59	0.15	3755	0.44	0.17	14378	0.45	0.20
Large class size	4150	0.15	0.13	12325	0.15	0.14	3755	0.26	0.22	14378	0.25	0.26
Overall STR	4150	1.07	1.73	12325	1.10	2.10	3759	3.88	7.00	14404	4.11	8.01
Scholarships	4150	0.00	0.00	12325	0.00	0.01	3704	0.06	0.08	14229	0.05	0.08
Library area	4150	106924.60	692858.50	12325	265202.30	1205000.00	3744	76026.02	241275.70	14378	55891.96	199016.40
Laboratory area	2818	238569.60	1006284.00	7625	175829.70	839886.00	0			0		
Computers	4150	2947.06	2559.82	12325	2705.45	2628.34	3759	1133.12	1434.84	14404	1330.65	1881.94
Average female	4150	0.31	0.11	12325	0.31	0.11	3759	0.23	0.13	14404	0.22	0.13
Average low	4150	0.09	0.08	12325	0.11	0.09	3755	0.09	0.08	14378	0.13	0.10

income												
Average high income	4150	0.18	0.10	12325	0.15	0.09	3755	0.19	0.15	14378	0.13	0.12
Average black	4150	0.03	0.03	12325	0.04	0.04	3755	0.04	0.05	14378	0.05	0.06
Average mixed	4150	0.18	0.13	12325	0.20	0.14	3755	0.15	0.12	14378	0.18	0.14
Average asian	4150	0.05	0.05	12325	0.04	0.05	3755	0.05	0.04	14378	0.03	0.04
Average indigenous	4150	0.01	0.01	12325	0.01	0.01	3755	0.01	0.02	14378	0.01	0.03
Average higher education	4150	0.62	0.14	12325	0.58	0.14	3755	0.55	0.18	14378	0.47	0.19
Lectures	4150	0.53	0.11	12325	0.50	0.12	3755	0.34	0.11	14378	0.31	0.11
Group work	4150	0.04	0.04	12325	0.05	0.05	3755	0.08	0.07	14378	0.10	0.08
Practical work	4150	0.03	0.03	12325	0.04	0.04	3755	0.07	0.05	14378	0.07	0.05
Seminars	4150	24.86	33.62	12325	23.14	31.95	3759	22.43	111.02	14404	28.25	128.58
Female faculty ratio	4150	0.38	0.10	12325	0.39	0.08	3759	0.36	0.13	14404	0.40	0.11

Table 14. *Per-pupil Funding Comparison, Public and Private Institutions*

	Public	Private	p-value
Per-pupil funds towards science/engineering equipment	17782.73	3532.27	0.05
Per-pupil expenditure, total	2175724	1491043	0.11
Per-pupil receipts	3119427	1541054	0.02

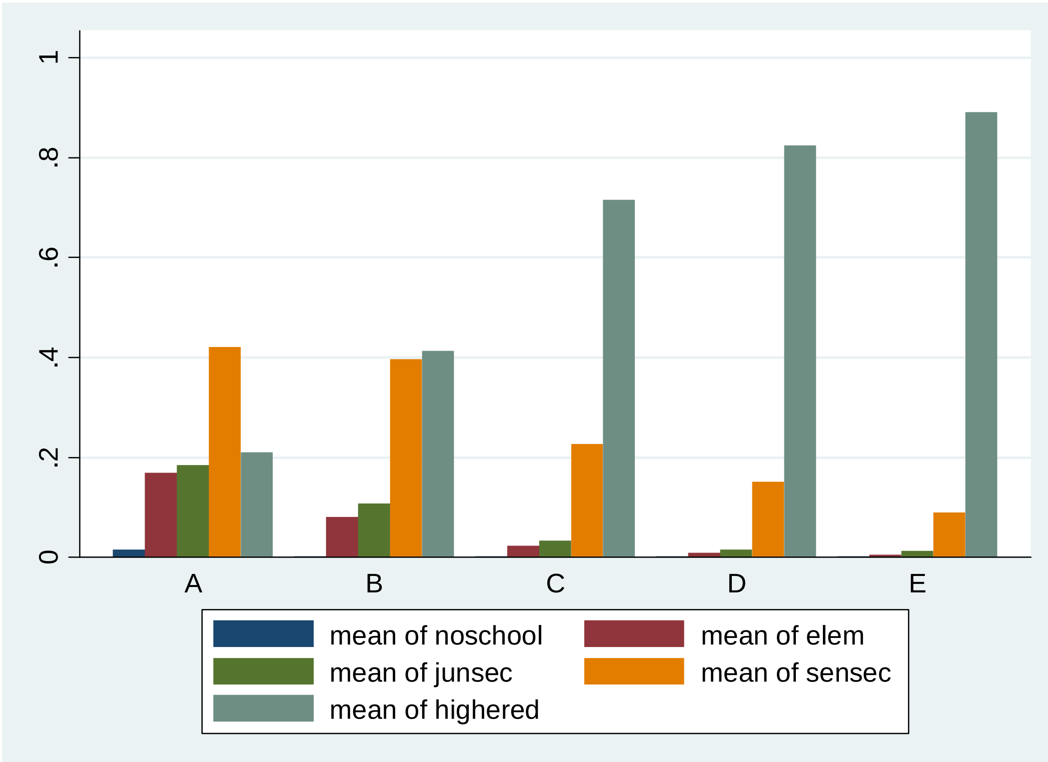

Figure 1. Parental Education by Income Levels

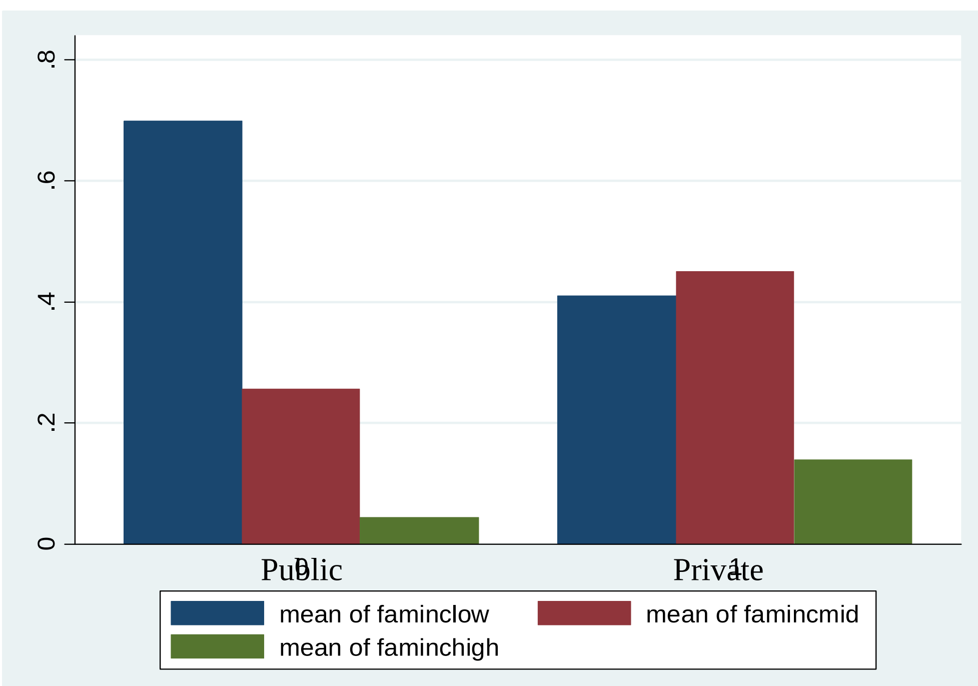

Figure 2. Family Income (Low, Mid, High) by Type of School

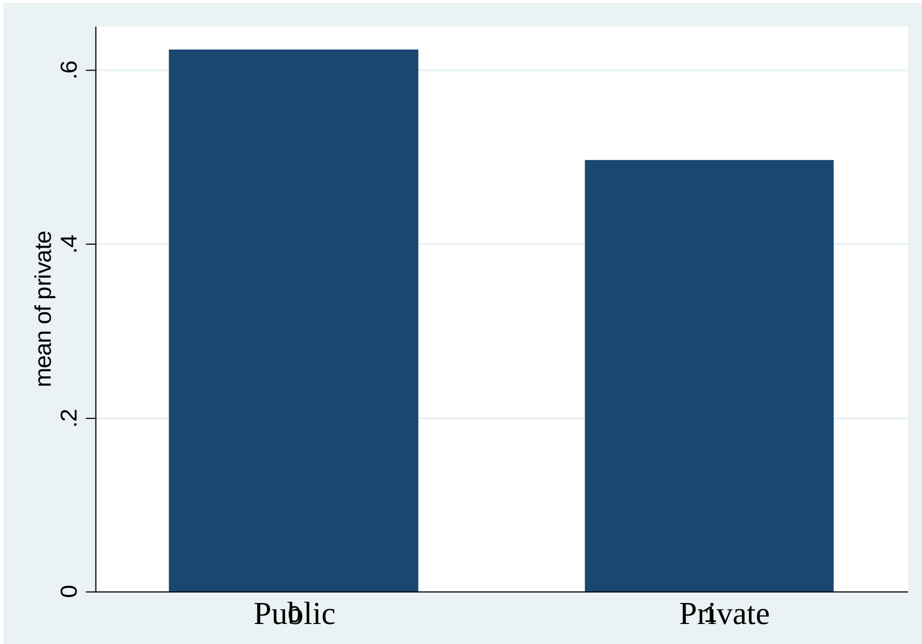

Figure 3. Private Primary/Secondary Schooling by Private/Public University

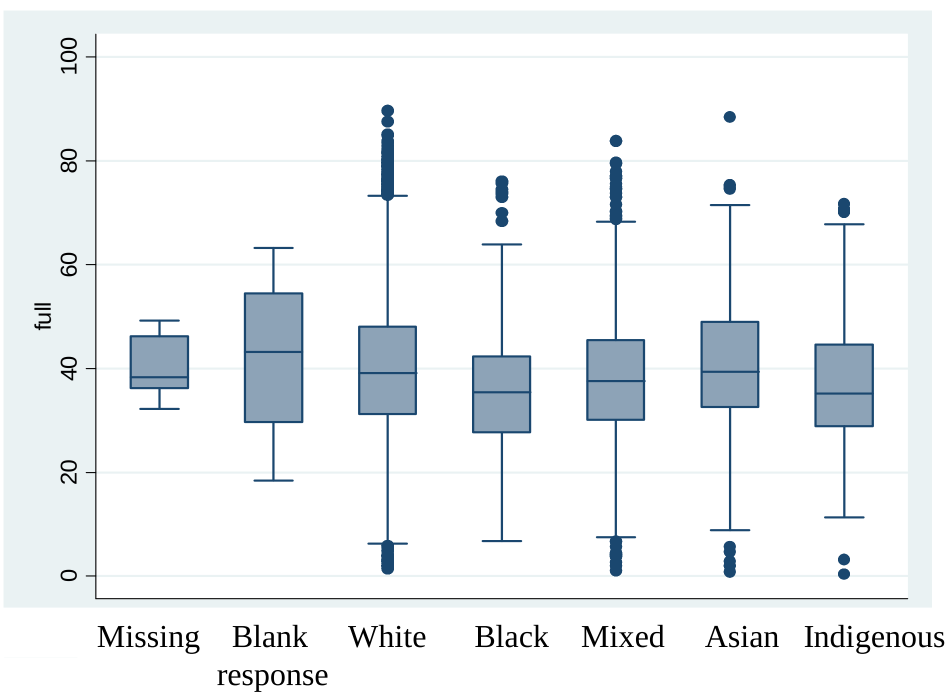

Figure 4. Achievement on the Full Assessment by Race/ethnicity

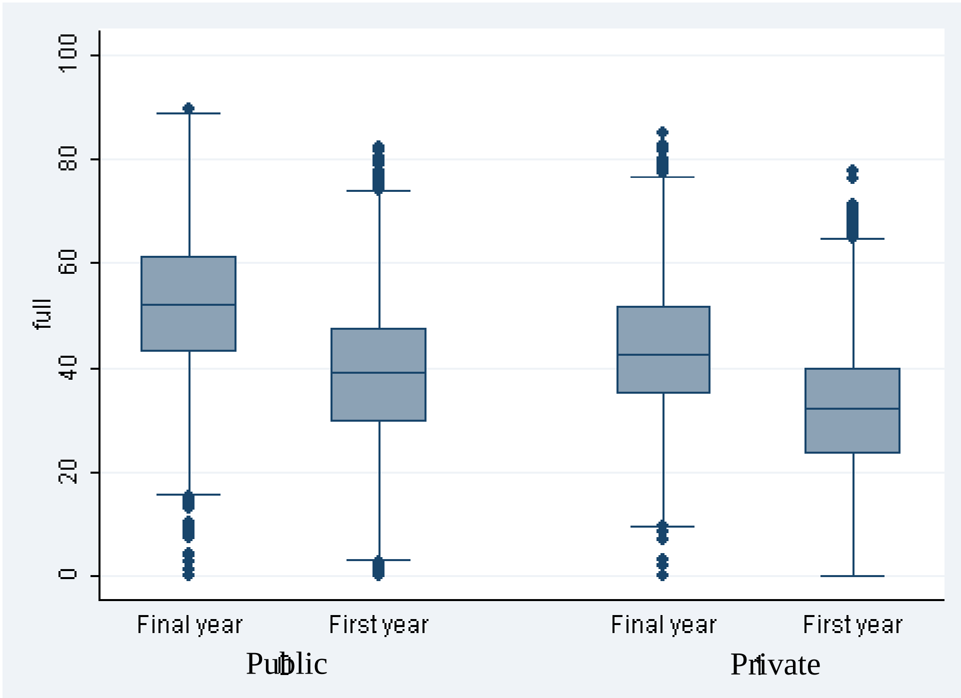

Figure 5. Incoming vs. Final Year Students, Public and Private Universities

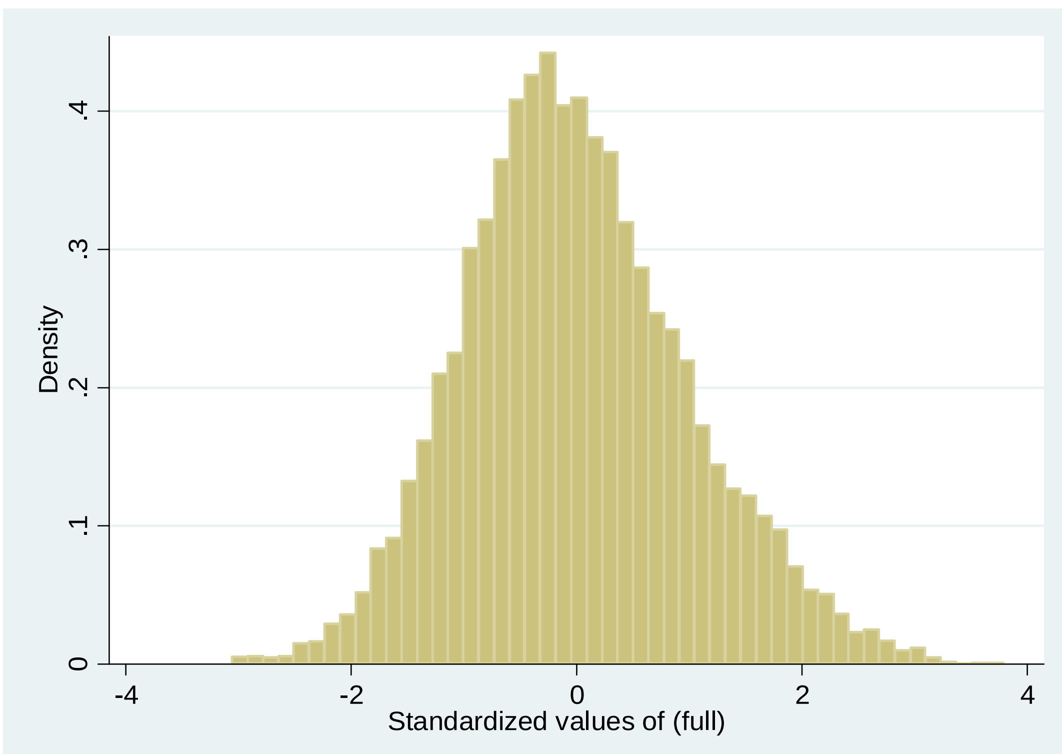

Figure 6. Full Test (Outcome of Interest, Blank Responses Removed), 2005

CHAPTER IV

HOUSES OF BRICKS: CAREER DECISION-MAKING FOR ENGINEERS IN GROWING ECONOMIES

Motivation

A street is crumbling in central Soweto Township. Ten miles away, at the University of Witwatersrand, top engineering degrees “address the social, spatial and infrastructural needs of a transforming South Africa” (University of Witwatersrand, 2010). And yet, the Soweto thoroughfare continues to darken into potholes—the Engineering Council of South Africa (ECSA) claims the country has only half the engineers necessary to meet development demands (O'Donnell, 2010).

Far from the noisy streets of some of Asia’s largest cities, bordering the wind-sheared plains of Inner Mongolia in Danjinghe, 103 square meters of wind turbines churn out 200 megawatts of electricity—purportedly part of a national wind resource capable of powering China to 2030. However, the same report describing the new lead China has taken in wind energy provision states from the beginning that the country still depends on expertise from Europe and America (Li et al., 2010).

Why are the countries extolled as rising development stars struggling to find citizens qualified to fill some of the most essential jobs? And, how can policymakers in these large, vibrant, newly-middle-income countries prepare locally-aware engineers to buttress the large and growing structures on which these nations increasingly depend? I develop a unique survey to provide one of the first pictures of the student choice process for engineering graduates. I then analyze survey data on student perceptions of engineering training in one of the BRICS countries to address this issue at the center of crisis conversations in nearly every country around the world.

Research Questions

In my study, I address the complex issue of student choice, engineering curricula, and international migration as well as the dearth of previous literature that answers these questions. I provide insight into the choice mechanism of engineering students in some of the fastest-developing nations as well as perspectives on the preparation these students receive to address local development challenges. I test two competing theories that might explain the dearth of relevant engineers—international conflict (the draw of jobs abroad) and local specialization (the lack of relevant training)—by gathering information from one of members (South Africa) of the extended "BRICKS" family: Brazil, Russia, India, China, South Korea, and South Africa.

I take advantage of a novel dataset to address pressing questions of engineering graduate labor market choices. I create and test a new survey on the decision-making process of graduating engineering students. I then conduct a survey of a sample of current final-year undergraduate engineering students at a major university on the choices they made leading up to their current positions, their perspectives on the training they currently receive, and their future aspirations. I look at whether it is the pull of the international jobs that top engineers have been trained for or the lack of a locally-relevant curriculum to provide engineering skills that creates the dearth in local engineering talent experienced by these burgeoning nations.

I ask generally, "Do engineering programs in developing countries train their students to address local development challenges?"

More specifically, I investigate the following:

- What factors do engineering students in South Africa identify as strongly influential in their choice of major?
- How well do engineering South African students feel they are being trained to tackle these engineering tasks?
- How well does satisfaction with locally-relevant training predict aspiration to a local career?

Hypotheses

I hypothesize that students would prefer to be motivated by a socially-conscious, locally-relevant occupation, but that because of a lack of curricular preparation, they turn to international opportunities. I further hypothesize that it is a lack of opportunity in the local labor market that precludes their entry into the national supply of engineers and leaves their home country without the STEM workforce it deems necessary.

Literature and Conceptual Framework

At a time when engineers are called upon to address the "Grand Challenges" of the 21st Century (National Academy of Engineering, 2010), the picture from the student perspective that my work provides is a novel and prescient perspective in the nascent field of engineering education (EE) research. To provide an overall context for the study of engineering student achievement, I describe the substantial debates surrounding international migration, the global engineering job market, and engineering training.

Two issues usually raised regarding engineering in developing country tertiary education are: (1) the human capital created at local universities is not retained, and (2) outside technical expertise is often needed since there is a lack of available human capital within the country. Is this a problem of supply or demand? Is the demand for local engineers and the commensurate pay not competitive at the international level, or is the trickling supply of applicable engineers at fault due to irrelevant curricula?

The "Giant Sucking Sound" of Brain Drain

Students choose to pursue careers in a given area for a host of reasons. Concerns abound regarding recruiting more engineers and holding them in the discipline (Walden & Foor, 2008). Even in the developed world, the questions of attraction, access, and retention of qualified engineers are raised. In the case of lower-income countries, high-skill labor migration is traditionally viewed as the malicious specter of "brain drain" on the sending country. This view argues that the Western world is sucking the developing world dry of its best workers because of several pull factors, e.g., higher wages and standard of living.

And, the question of having too few engineers is compounded by having under-qualified ones. Talent and skills are highly sought after by employers. An international poll of human resource managers in 2006 found that three-quarters said that attracting and retaining talent was their top priority; some 62% worried about company-wide talent shortages (Woolridge, 2006). This problem is cited even in Asia's large and burgeoning economies. A broader awareness of world issues and international experience have become more desirable for students and future employers alike (Continental Corporation, 2007). A huge number of students are studying abroad (Organisation for Economic Co-operation and Development [OECD], 2007). Engineers, even locally-specialized ones, must also be aware of the world around them. Certain questions, e.g., climate change, point to globalized problems as well as solutions. Questions and relevant research can no longer be confined to certain locales, especially in science (Young et al., 2006).

However, there are few studies of the complex decision-making process that leads to this overall trend. Some point out that there are actually positive outcomes of international migration that reduce the effects of the “brain drain”. Advances in technology over the past decade have helped to accelerate the idea of “brain circulation” through the development of sophisticated information and communication technology and through the liberalization of many of the global markets (Saxenian, 2005). Though arguments are made that both the sending and receiving countries benefit from the migration of talent, researchers (e.g., Hart, 2006) point out that some countries are still at-risk for losing investments made in human capital and having adverse effects on development. Countries are becoming proactive about recruiting their talented diaspora back. For example, China is implementing “Plan 111” to create a “Brain Gain” and recruit leading scholars to China (Li, 2006). A new report on Indian and Chinese returnees from the US suggests that very few want to stay in their adopted country (Wadhwa et al., 2009). In another report, this is only 8% for Indian respondents (Finegold et al., 2011). In Sub-Saharan Africa, graduates from higher education “account for less than 3% of the labour force but more than 35% of all migrants” (Leveraging Migration for Africa).

Few studies have addressed individual choice and the relevance of the curriculum in studies of international migration, let alone focusing on engineering education. In my study, I test the significance of this first theory by asking students about competitive international offers and their consideration of global factors as they navigate the educational pipeline.

The Elusive Value of Specialization

Opposite brain drain, the problem faced by the BRICKS may be the lack of relevance of the local curriculum in training specialists. Bowman (1962) describes the course of development for America's land grant colleges, which were faced with the challenge of relevant "human resource creation", needing human capital trained to address particular development needs. In many ways, the BRICKS face a similar challenge in their national higher education policy agendas today. They have development needs to be answered by their engineers, but students may also need different training for the global marketplace.

"Grand challenges" in engineering point out the potential for engineering to solve major problems for the world. Many of the challenges are pressing issues for development (National Academy of Engineering, 2010). Growing and changing demands on engineering graduates have made the skills needed a more complex field to navigate. The United States, for example, adopted new accreditation criteria that call for student-centered pedagogies and preparation in soft skills; a National Academy report outlines new skillsets needed for the "Engineer of 2020"; and a survey of college administrators and employers corroborates this (ABET; NAE, 2004; NACE, 2004). Students are looking for professors who would deliver and possess these same skills (Morell & DeBoer, 2011).

But, there is still a dearth of highly-qualified engineers and scientists to address local needs. Locally-sourced knowledge and the inclusion of local stakeholders are assets to development projects (Bray, 1999). Developing countries either do not have the capacity to train local talent (e.g., Mozambique: Hood, 2002), or they must watch the flight of their top intellectuals to pursue work and study outside the country (e.g., South Africa: Hagopian et al., 2004). The tug-of-war between local relevance and global applicability is omnipresent.

Localization may provide benefits for innovation and relevance (Andersson, Quigley, & Wilhelmsson, 2005), while a globalized perspective may allow employees to be more adaptable (Organisation for Economic Co-operation Development, 2007). Cheng (2005) recommends a hybrid model that takes global issues and adapts them to local needs. Moving forward from Bowman (1962)'s discussion of appropriately designed higher education structures, the information gathered here looks at the possibility for national investment in engineering to "focus on competence building to enable Africa [or the other developing economies studied here] to solve its own problems" (Juma & Bell, 2006). If students are trained to best address localized problems, they may stay in the locale where they are both useful and have important social networks. I test the relevance of this second theory by including survey questions on the training that students receive and the factors (including social networks) related to their choice of major.

National and International Engineering Markets

International standards and globalized competition come up frequently in this literature as goals for countries to benchmark their progress and as helpful guidelines to addressing local problems. The Washington Accord, the first international agreement regarding mutual recognition of engineering qualifications (1989), may facilitate brain circulation. Included in this agreement are clauses addressing comparable accreditation procedures, mutual monitoring, and goals for development. This accord was followed by a number of additional agreements regarding issues such as technical degrees and student exchanges.

Full Members:

Australia (IEAust)

Canada (CCPE)

Hong Kong, China (HKIE) – 1995

Ireland

Japan (JABEE)

New Zealand (IPENZ)

*South Africa (ECSA)

United Kingdom (ECuk)

United States of America (ABET)

Provisional Members:

Chinese Taipei

Germany (ASIIN)

Korea (ABEEK)

Malaysia (BEM)

Singapore (IES)

The only BRIC country on either list is South Africa, a full member of the Washington Accord. I investigate the South African situation in more detail here.

Who are the "BRICKS"?

In late 2001, the Goldman Sachs Global Economic Center released a working paper extolling the huge economic potential of four developing countries—Brazil, Russia, India, and China (O'Neill, 2001). Over the next decade, the term "BRIC" became a ubiquitous descriptor for the four rising stars of the developing economy pantheon. Since the publication of the "BRIC" working paper, other developing countries have jostled to join the list; inclusion in the "BRIC" family portends a country's promising development future in the international arena. South Korea has publicly maneuvered to be added, and Turkey has been considered. South Africa is frequently cited as an important middle-income country example, and, more importantly, in the BRICS group it represents the forgotten continent of the Global South—Africa. A recent McKinsey report even noted its place at the head of the “African Lions” (Roxburgh et al., 2010).

South Africa’s particular history manifests itself in the issues of diversity that current policymakers in higher education must address. Issues of access focus on affirmative action programs and remedial programs. d’Almaine and co-authors (1997) point out that, even today, though traditionally segregated technikons are becoming mixed, their racial make-up still reflects their apartheid-era status, and there is much less opportunity for blacks. Overall, South Africa’s basic tertiary access is not as central an issue as it is elsewhere in Sub-Saharan Africa ([SSA] Teferra & Altbach, 2004). The country has a national-level board focused on the structure of engineering education, the Engineering Council of South Africa (ECSA). The ECSA explicitly states that one of the purposes of engineering is national development (ECSA, 2008); my study presents the students’ evaluation of this point.

Systematically connecting sectors within countries is vital: “The most damaging legacy of the African system of higher education is the separation between research, training, and practical activities” (Juma & Bell, 2006). African leaders recently gathered to discuss points to increase the preparation of university graduates (an increasing number) for the labor market, including emphasizing local university-industry partnerships (Association of Commonwealth Universities, 2011). A recent document review and analysis on the connection between higher education and development also underscored the need to connect higher education actors to other political and social actors (Higher Education Research and Advocacy Network in Africa, 2011).

These questions are only more recently gaining attention, so there is not a lot of rigorous academic work (e.g., Waghid, 2000; Case & Jawitz, 2003; d'Almaine et al., 1997) available. In engineering training, theory and practice may be mismatched (Waghid, 2000; Ensor, 2004). Overall, South Africa's basic tertiary access is not as central an issue as it is elsewhere in SSA: "South Africa, with more than half a million students in its twenty-one universities and fifteen technikons (post-secondary vocational colleges), is third in the number of enrolled students on the continent" (Teferra & Altbach, 2004). South Africa has a "practicing engineers per capita" of 1:130 (World Economic Forum, 2001) and a GDP per capita of 9,736 (by World Bank GDP, World Bank, 2007). The University of Cape Town is one of South Africa's oldest universities, a flagship public institution. I focus on this university as an exemplary engineering program for the country.

As the number of tertiary students continues to massify (broaden access to education), policmakers struggle to create learning opportunities that are relevant and beneficial. Banya & Elu (2001) conducted a longitudinal qualitative study looking at African higher education funding through the World Bank. Their findings pointed out that even with greater emphasis on higher education in budgetary allotment, high student-faculty ratios persist in these areas, where demand for access to tertiary education is large and growing. Adewumi (2008) discusses the example of agricultural engineering. Agricultural engineering, while necessary for developing nations, may be available and necessary, but these engineers are often marginalized. Unemployment for the greater and greater numbers of engineering graduates partially results from incoherent national education policies. A final concern, and one of the most important that comes up, is the high cost of the specific needs for engineering training. Engineering entails high-cost training (e.g., laboratory equipment). As Juma (2007, p. 7) points out, “most of the universities that exist in Africa were originally designed to support nation building. The challenge today is community development.”

Calls for change often point to connections with business and entrepreneurship training. Examples often cited of best practices for development in Africa include Ghana’s University for Development Studies, the University of Zambia, and the Kigali Institute of Science, Technology and Management, which focuses on advanced research responsive to local needs. Knowledge is frequently cited as being important to a country’s economic development. More recently, it has been argued that increased globalization has made knowledge-based development even more pressing for reasons of competitiveness. Knowledge, rather than natural resources or manual labor, is valuable for both its adaptability as a resource and its relevance to contemporary industries. The concept of a knowledge economy emphasizes exploiting knowledge in a flexible, agile way in order to respond quickly to the global economy and to take advantage of partnerships within nations and with other countries. Often, the progress of a knowledge economy (KE) must be incremental, and it must necessarily be highly context-relevant to the country in question. Because of KE’s implications for today’s global economy, moving towards or sustaining a nation’s knowledge economy is important for both developed and developing countries (World Bank, 2007). These and other supporters mentioned argue implicitly and explicitly that the purpose of education is to train students to be skilled workers for their own good and the good of the country (Camacho & Cook, 2007), and that the country's economic competitiveness depends on its innovative capabilities.

While this work is situated in the decisions national policymakers make in training and retaining talent, ultimately the decisions are made at the individual level. Students face a number of factors in their decision-making process—both when they enter school and choose a major and when they choose where their career will take them upon graduation. I note this literature in the creation of the survey below.

Definitions

The demands on engineers today include innovation to a great extent. As defined by the new *Innovations: Technology, Governance, and Globalization* journal in its inaugural issue (Auerswald & Quadir, 2006, p. 4), innovations are "the efforts of individuals, groups, and communities who creatively employ new organizational forms, and in many cases new technology, to effect discontinuous change." This is not only in curricular content and skills taught (e.g., Brophy et al., 2004, creativity, Schumpeter, 1928, Amabile et al., 1996; Davila et al., 2006; critical thinking, Luecke & Katz, 2003) but in teaching practices as well (Fletcher, 2007).

Technology, here, refers to engineering specifically and to the innovation component of the "knowledge economy" more broadly. Further, technology in these conversations often means infrastructure, but it has implications more largely for poverty reduction, agricultural challenges, and sustainable development, which are being addressed more and more in the literature. Juma & Bell (2006, p. 2) define “infrastructure” as “the facilities, structures, associated equipment, services, and institutional arrangements that facilitate the flow of goods and services between individuals, firms, and governments”.

Conceptual Framework of Student Engineering Choice and Practice

I build on previous work that underscores the importance of understanding the student perspective on their environments and on the factors that matter for student decision-making. I first ask for the student to provide definitions for the terms that they will use in the interview. Understanding how s/he defines the “local” space in general (e.g., family? parish? district? nation? [Kepe, 1999]) and in scientific terms (e.g., a community water resource, a national pollution policy; Calheiros, Seidl, & Ferreira, 2001) is central to understanding how they navigate these boundaries. I also ask him/her to identify the characteristics of the engineer who would be best suited to answer relevant challenges.

I then ask a number of questions about the student’s previous decisions in choosing a track, a school, and a major. What opportunities were available in secondary school? What incentives were provided for different opportunities? I ask him/her to identify important influences (e.g., family) in these choices as well (Bourdieu, 1977). I also ask about the student’s perception of his/her own ability to choose between options.

Engineering students also identify their perceptions of the training they are receiving. First, they discuss the curricular preparation they are receiving (student evaluations of curriculum; importance of curriculum; comparing importance to emphasis in program; Guest et al., 1999)—they discuss areas such as communication, content knowledge, critical thinking, research, teamwork, adaptability, cross-cultural understanding, problem-solving, using ICT, creativity, rank order of importance of skills, extracurricular opportunities, practical opportunities, study abroad, guidance/mentorship (Texas Higher Education Coordinating Board, 2010; National Academy of Engineering, 2004; Dassault Systemes and the Student Platform for Engineering Education Development, 2009; Morell & DeBoer, 2011).

Finally, looking to the future, I ask about career aspirations in college. In what area—international vs. local opportunities—are students focusing their searches (De Grip, Fouarge, & Sauermann, 2009)? Do they perceive migration to be a problem? How do they perceive the career path, and do they plan to stay in an engineering career at all? (Hunt, 2010) And, were they prepared for the career's needs and provided with guidance in this process?

I end the survey with a series of background factors that, based on my overall conceptual framework, are important determinants of the student's and the household's educational choices (e.g., scholarship status, parental occupation). I also ask about the student's current career focus in his/her major.

Data and Methods

Survey Information

My survey gathers student self-reports on their decision-making process, their current attitude towards EE, and their future aspirations. This survey is developed from an interview protocol that was tested during an interdisciplinary qualitative methods research course where I investigated the educational decisions made by Bangladeshi and American earth sciences students. I draw on previously-used surveys by the state of Texas (Texas Higher Education Commissioning Board, 2010) as well as on a framework developed to investigate engineering student retention (Anderson-Rowland, 1997). This question has not been applied to look at the whole process of engineering education and the engineering pipeline for students around the world before.

Independent variables—which here serve as groups for t-tests—come from demographic information (age, race/ethnicity, gender, parental education, etc.) provided by respondents. Dependent variables include Likert-scale identification of the pre-college factors influencing the students' choices of major, evaluations of how well the current curricula prepares students to answer local development challenges, and an index of future career aspirations. Further, demographic background characteristics of respondents will be gathered at this point and compared to the known indicators for the university.

Prior to embarking on data collection work, I conduct cognitive interviews with engineering students and administrators in the United States and South Africa to test the instrument. In compliance with the Institutional Review Board of Vanderbilt University, informed consent will be obtained from students taking this survey. Students will be made fully aware of the voluntary nature of their participation. Appropriate steps to ensure the protection of privacy are taken.

Analysis

In order to understand the choices, experiences, and aspirations of engineering students in developing contexts, I gather cross-sectional survey data on a sample of students graduating in the engineering majors. The sampling frame for my study consists of two stages. The primary sampling unit is the faculty or college of engineering. Here, I take a purposive sample from institutions that I can reach and that have agreed to participate in this first study. This study focuses on information from the University of Cape Town (UCT), which I pointedly select. I distribute the survey to all graduating engineering students. In the 2011 class (graduating in December 2011), there are 500 students. Within the selected university, the sampling frame of final year students is drawn from administrative records in coordination with UCT's Ethical Research Board and engineering department administration. I have a response rate of approximately 11%.

The cross-sectional data from the survey provide a useful representative look at, on average, the most important background factors for students, their perceptions of how well their programs prepare them to address local problems, and their future goals. I conduct one-sample t-tests for each country to confirm or reject my hypothesis that specialization is the ideal driving factor. With the addition of background information on survey respondents, I can determine how closely school experiences are associated with future aspirations and how these break down along demographic lines.

Limitations

One major limitation is the particular context of this institution. The University of Cape Town is not a representative sample of universities in South Africa—it was purposively sampled as a convenient site and as one of the flagship, international institutions in the country.

Nor are the students who filled out the survey necessarily a representative sample of the students at UCT. Self-selection out of the study may also threaten the analysis. To mitigate this, the survey was offered online for convenience, and respondents were automatically entered to win a nominal prize. However, the response rate was approximately 11%, and the group that chose not to respond may be systematically different from the group that did.

More broadly, the group that I sample is not representative of the group that started their first year at UCT together. The students in my study are necessarily already on the engineering track; I am able to generalize to the population of students who, at an early age, may go into this field, but not to all students trained in the country; primary and secondary education may be important turning points, but I only look at the perspective of those who chose to finish studying engineering in university. This study adds to an overall understanding of the engineering pipeline, but only from the perspective of those who have made it to the end. Even here, students face barriers to their continuation in engineering as they would desire, and they are wooed away by outside incentives.

Results

The survey asks students about three dimensions of their engineering study and career choice. First, I ask about factors leading up to their choice of major. Within this dimension, students give their perspective on two constructs: factors that influenced their choice and the relevance of their pre-tertiary training. They rate the importance of factors that went into their decision to pursue engineering, and they rate the frequency of local science and engineering topics and teacher knowledge in local topics. The second dimension is the student's current college training. Constructs within this dimension include the quality of university resources for their training, the effectiveness of their training versus the importance of the skills imparted, and their current awareness of engineering in local or global space. The third dimension is the student's choice of job. The constructs within this dimension on the survey include the offers received, the attractiveness of jobs in local or global spaces, and the obligation the student feels to work in different spaces.

In addition, I note how students define the "local" space and how they believe the local engineering job market should work. Students answer questions about the constructs of local space and local engineering problems; they describe which areas can be categorized as "local", "global", or "in-between", and they give an example of a "local" engineering problem. They also provide their perspective on the "ideal" worker for local engineering jobs and the reality of the local engineering workforce.

Defining Local Space

South African students define the "local" space as an administrative demarcation smaller than a state/province. The household, neighborhood, and city are all local. The state, nation, and region are "in-between", while the region, continent, and world are "global". Figure 1 illustrates the transition in perception from "local" to "global" spaces. While South Africa shares strong cultural connections to other countries in southern Africa and in sub-Saharan Africa more broadly, areas outside of the national level are seen as "global".

Students give examples of "local" engineering problems that focus on examples of basic living needs. Many responses mention "energy", "water", and "sanitation". Few responses mention "basic engineering problems" such as "find stress on a beam" or "build a building". They evoke a conceptualization of a community with a deficit, one that "lacks", whether it lacks electricity or other services. On the other hand, they refrain from using terms that indicate higher technology, increased efficiency, or movement towards an ideal level of development. Rather, they focus on bringing up an environment to a minimum level, e.g., "provide adequate sanitation". Answers referring to improving "poor transport" systems are frequent, where "increasing efficient traffic flow" are rare.

Choice of Major

Ratings of influences. Students rate the influences they felt when deciding to choose engineering for a major. On a scale from 1 to 10, they give ratings to the factors cited in previous work as influential on undergraduates' decisions to enter and stay in an engineering degree. For graduates in South Africa, the highest influence was that engineering offered interesting work. The next highest was the challenge of solving problems, and only after this came references to the marketability of the profession around the world and the surfeit of job opportunities.

Additional reasons for choosing engineering. Numerous students provided additional reasons that were not encapsulated in the reasons accrued from previous studies. These additional reasons were all aspirational; they referenced a great deal of intrinsic motivation on the part of young engineers. The students spoke of passion and creativity, personal challenge and improvement, and development for themselves and their communities.

For example, one student wrote the following:

"I found engineering late in life – having not really understood what it was at all, and learning that I loved it. I wish I had been given an opportunity to find out more earlier."

Another said:

"The most important factor [as to why] I did engineering was to influence and develop technology that helps preserve natural resource and also improve global quality of life (starting locally)".

Relevance and quality of primary/secondary school. Students rated the relevance and quality of their high school experiences as higher than in primary school. They received more exposure to local science and engineering topics in high school. Further, they received significantly more exposure to engineering than in primary school. In primary school, the difference between locally-relevant science and locally-relevant engineering exposure was significant (with science being higher). Overall, teacher knowledge of local topics was rated below "somewhat knowledgeable".

Training

University resources. Students rated their professors overall as fairly good teachers and above-average engineers (means of 7.41 and 6.94, respectively). The students who responded to the survey had taken significantly more local internship opportunities than they had global exchanges. (The range of local internships was from 0 to 6 with a modal value 0, had 38 students and a secondary mode of 2. Exchange opportunities ranged only from 0 to 2, with only one student going abroad twice.)

Effectiveness of training vs. importance of skill. For all of the skills listed on the survey, students rated their realized training as less effective than the importance they assigned to the skill. Of particular note, the coverage of global problems, hands on experience, training on local topics, the coverage of local cultural issues, and training to work internationally were all significantly lower ratings than their importance indicated. The most effectively taught domain was the coverage of global issues, followed by hands-on training and local topics, then training to do international work, and finally local culture. Students also rated training on local culture as the least important skill for future work. On the other hand, they rated hands-on training as the most important, followed by global issues.

Student's awareness. There were few significant differences between students' personal identification with a given space and their familiarity with engineering practice at that level. One exception was the significantly higher ($p = 0.58$) sense of personal identity than familiarity with engineering practice at the city level. And, at larger demarcations, students were slightly less personally attached but more familiar with engineering practice, while at lower levels the opposite was true.

Choice of Job

Offers. Students received significantly more local offers than job offers abroad. Still, many students listed only one or two offers in both categories.

Attraction. There was not a significant difference between the attractiveness of a local versus a national job across the dimensions of attractiveness for job seekers. However, between the local/national levels and the international level, there were notable differences in which dimensions would be "pull" factors as students entered the job market. The local levels were significantly more appealing in the dimensions of familiarity with issues and family. On the other hand, the global level was significantly more appealing for reasons of technology and wages. (See figures 4-6.)

Obligation. Students were asked to rate the level of obligation they felt to work in either a local or global space. There was no significant difference between their levels of feeling obligated to work in either space.

Opinions

Despite finding no difference between students' personal feelings of obligation to the local context, their opinions of local training for engineers are strong. Their assessment of how important it is for local engineers to work locally was significantly higher than the frequency they cited as reality. They believe that it is important to train local students to address local engineering problems (mean of 8.35). But, their ideal for engineers working locally does not match up with their perception of reality.

Discussion

After summarizing the numerous results of the study above, I discuss the overall answers it provides to my research questions. I contextualize my study within the broader literature, and I provide directions for future work.

Implications

Student responses do not indicate a simple "push/pull" dichotomy. Their choices are not made solely on the lack of relevant locally-relevant training or the preponderance of high-paying international opportunities. Instead, motivated, qualified engineers are being reluctantly drawn to areas that may be less socially valuable but that have more immediate relevance for them.

In addition, there is a competing local market that exists outside socially-conscious, locally-relevant engineering positions. Students may work in local jobs, but they may exit the engineering sector for higher-paying jobs in finance.

There did not appear to be a significant difference between graduates of different sexes or scholarship statuses on how obligated they felt to work locally. However, there did appear to be significant differences between students who identified as different races in how obligated they felt to work locally (Table 1). The three main racial/ethnic groups in the sample that are often under-represented in engineering felt a higher sense of obligation to work locally than the white/Caucasian/European graduates in the study. Similarly, white/Caucasian/European graduates did not rate "local needs" or "number of job opportunities" as highly as factors that determined their choice to go into engineering. (There were not significant differences by race in ratings of the primary/secondary training received.)

Technological capital. Students exhibit a desire to act locally, but they note a lack in mechanisms that are relevant to them. There is the potential for locally-grown technological capital to be applied, but the final link between a student's training and the need for that individual in the local context is not clear.

As can be seen from student responses regarding the ideal and the reality for local or foreign engineering to practice in their community, it is not that students perceive there to be too many foreigners—it is that there are not enough local engineers who work in these jobs. Students' training is highly theoretical, and while they receive adequate training on skills for working in a global environment, hands on opportunities for local work are scarce despite student interest. They have the passion, but they do not have the personal investment in being part of the local engineering workforce they recognize as necessary.

This lack of connection between motivated graduates and the jobs they are needed to fill reflects a lack of what Grossman and colleagues (2009) term "pedagogy of practice" in their preparation to work in engineering. In particular, students report few "approximations of practice" (Grossman et al., 2009) that provide students the opportunity to see their skills as they would be used in areas of high need for local development. Without this active learning, students do not understand the pathway by which the theoretical concepts they have learned can be useful, though they may understand the need for engineers to address development challenges.

Policy measures. Policy measures the build on this passion and cultivate a personal relevance to engineering training could directly address the dearth of locally-trained, qualified engineers. Though the primary school context offers ample opportunity for beginning to instill an understanding and valuation of local engineering, those opportunities are not provided.

Practical classes are important component of the engineering curriculum, and students note they need improvement. Connect these practical classes to pressing local issues as well as to local industry, providing a possible source of funding and a guaranteed local job opportunity.

In addition, students could be encouraged to take advantage of their global training to go abroad, but incentives could be put in place to bring them back to practice in South Africa. Finally, support for the creation of one's own opportunities—entrepreneurship—could encourage individuals to engage in economic development that benefits their community and future generations of engineers. A major missing link in the scope of the implications of chapter 3 is the lack of perspective on the importance of the job market in the selection process for students. Chapter 4 underscores the importance of the job market from the student perspective. Implications of this work in its recognition of the need for practice in the profession of engineering extend beyond just this discipline. As Grossman et al. (2009) note, other disciplines have the same challenges with a lack of opportunities for practice. Engineering, among other disciplines, recognizes the need for hands-on opportunities during the education process that are meaningful to the student and useful for society in the future (e.g., ABET, 2011); however, engineering education, as with other disciplines must adapt its learning culture to incorporate practice in its conception of educational excellence.

It is not just a problem of demand for engineers in socially-relevant jobs. The reason for a recommendation for local incentives is the lack of supports in the local engineering culture to foster students' application of their knowledge. Even at flagship universities in the United States (e.g., the Massachusetts Institute of Technology), students may see a lack of applicability in the skills they learn to the jobs to which they aspire (Felder & Brent, 2003).

Future Work

In the future, I will extend the survey in terms of countries and in the dimension of the institutions represented within countries. Policymakers around the world voice their need to recruit and retain a highly-qualified local engineering force. Broader surveys of this kind would give insight into the actual decision-making process of recent graduates.

A number of structural, institutional, and personal factors contribute to the achievement outcomes of engineers and the choices young people make that determine their future career paths. This study focuses on the concerns of fast-growing economies. Often, developing contexts are left out of major discussions of fine-tuning engineering training. Society's greatest challenges may be answered by engineers, but this will only happen if we are aware of improvements that need to be made in engineers' intellectual and practical preparation.

The implications of this study extend most directly to other rapidly-developing economies. The students expressed the tension they themselves felt between international competition/global competence and local specialization. They were inclined toward selecting the emotive import of local problems as a priority, but not one would discount the need for international perspective. As countries balance local infrastructure needs with mounting demand for equal integration on the international playing field, they must understand why precious human resources may not end up in jobs that immediately serve national needs. The external validity of this study extends to the broader international community, though. In any locale, the tools of the intellectual toolbox must fit the job at hand. Regardless of the country's income level, nations jealously guard their engineers. Administrators would do well to understand what predicts student achievement and what drives these students to embark on the lives they choose to lead.

Engineering education itself is a young field, and there are bountiful opportunities to explore unstudied subject areas. However, the perspective of students and a rigorous understanding of student learning are often left unincorporated in the investigation of access, persistence, and labor market outcomes. This work builds on the foundation of a new, prescient field by using a dataset incomparable in tertiary education anywhere in the world and by soliciting data from stakeholders previous research has largely left untapped.

Figures

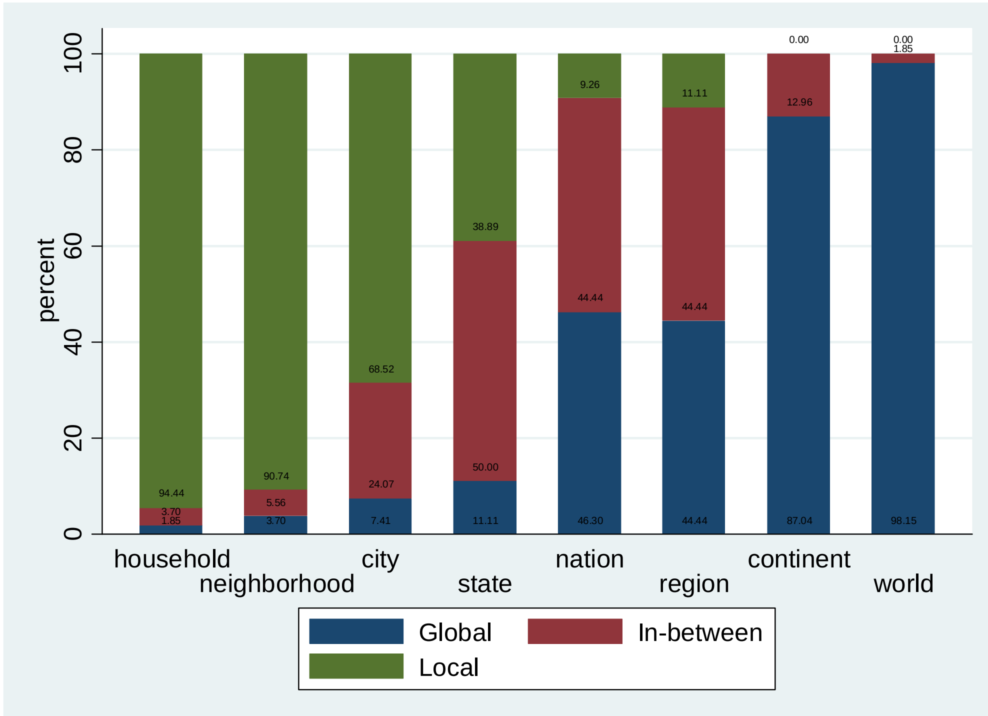

Figure 1. Identification of Local, In-between, and Global Spaces

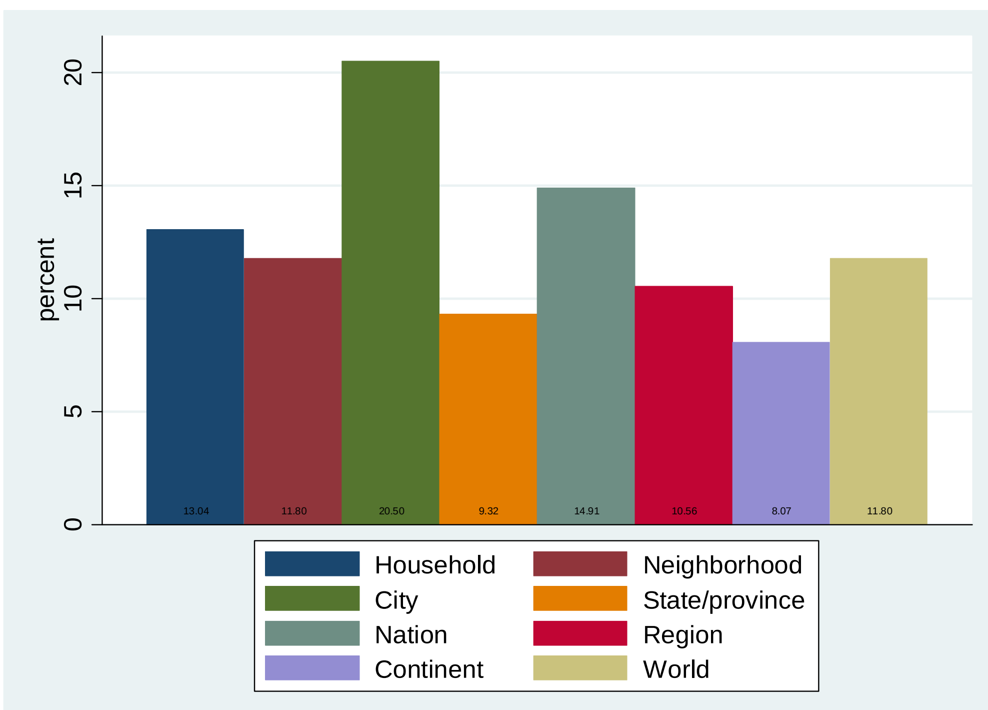

Figure 2. Areas with which respondents most closely identify

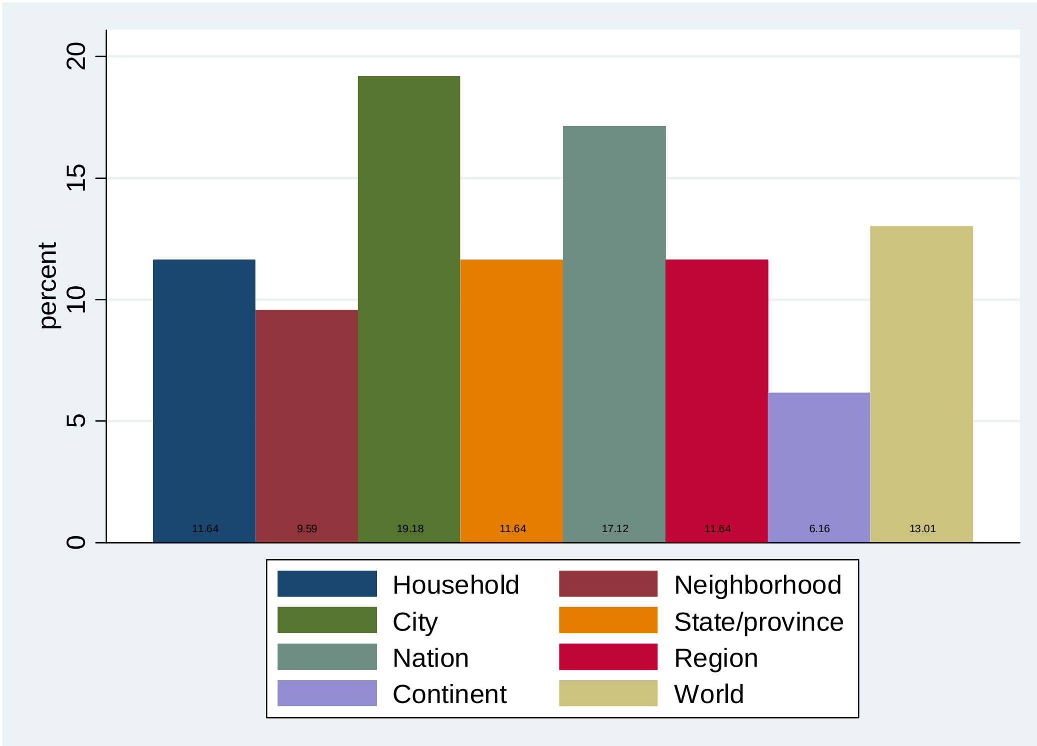

Figure 3. Areas of Engineering with which Respondents are Most Familiar

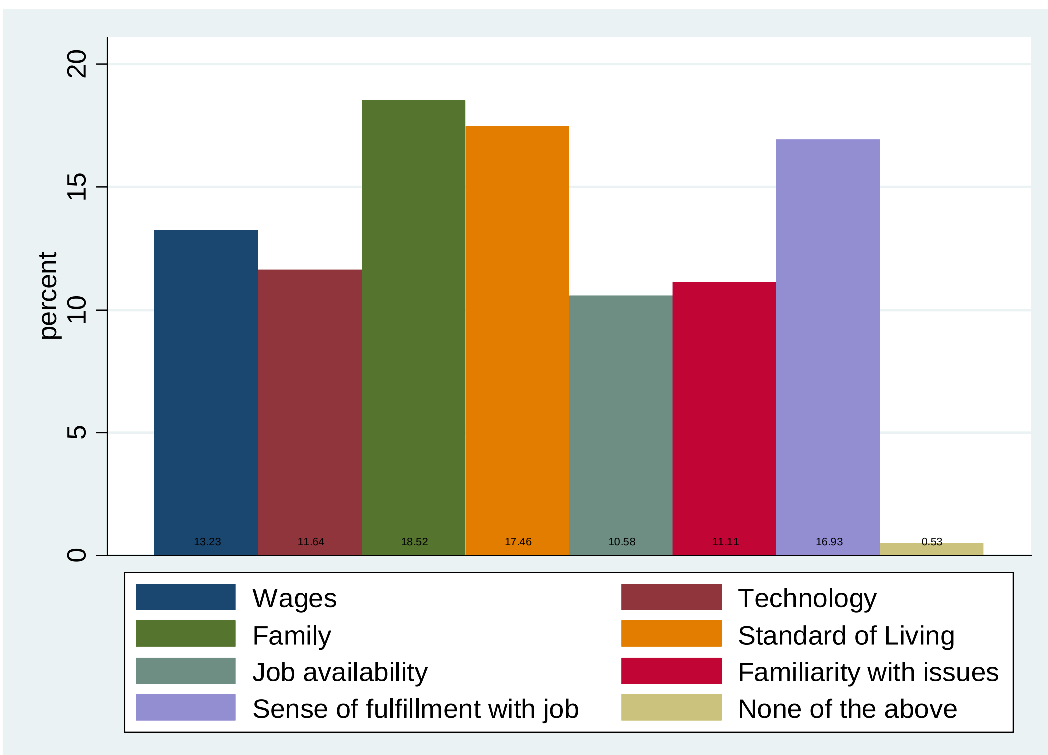

Figure 4. Reasons Given for Attractiveness of Local Engineering Job

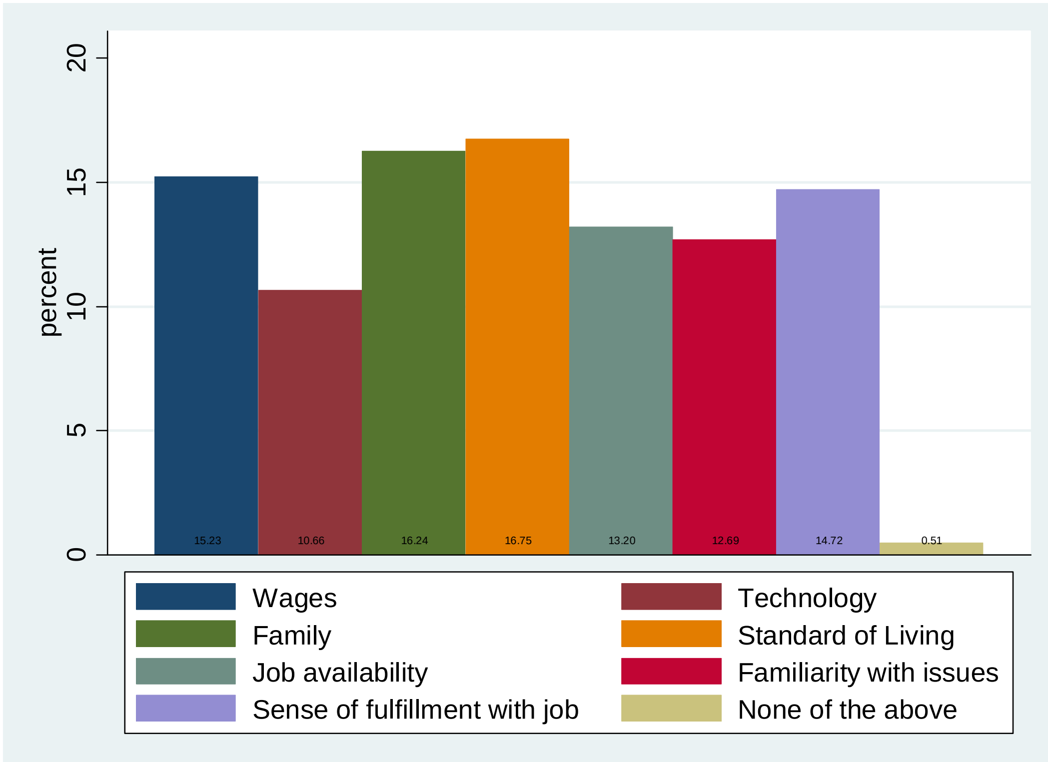

Figure 5. Reasons Given for Attractiveness of South African Engineering Job

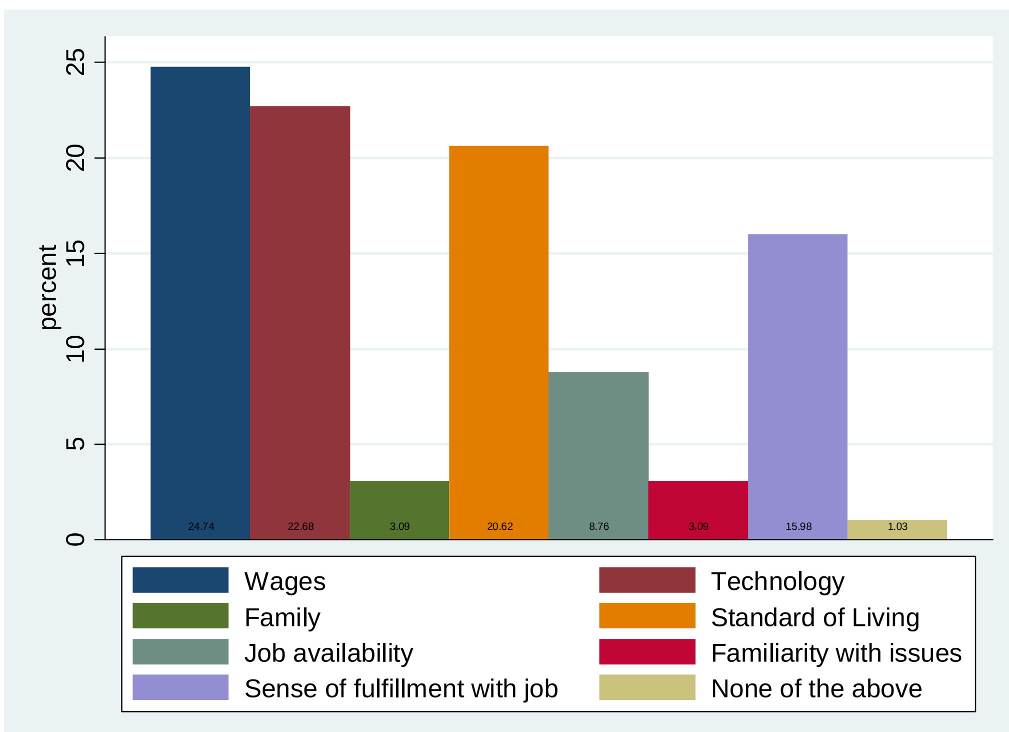

Figure 6. Reasons Given for Attractiveness of Global Engineering Job

Table 1. *Racial Differences in Obligation to Work Locally*

Race/ethnicity	N	M	SD
White/European/ Caucasian	24	4.79	2.34
Black/African	16	6.5	2.80
Indian	5	7	2.45
Colored/mixed	7	7.86	0.90
Other	2	7.5	0.71

Note: ANOVA gives F-statistic $p = 0.02$

Appendices

Appendix A: Survey Protocol

Engineering graduate survey

You have been selected for a survey on the quality of your engineering training. This survey's purpose is to understand how well universities prepare their engineering students to address development challenges. This survey should take less than 20 minutes. Your responses are very valuable, and they will help further our understanding of how to structure engineering education. If you complete the survey and enter a contact email address, you will be entered to win an iPad. You are under no obligation to participate, though. Thank you very much for your time and knowledge. Consent information is given below. Click "Continue" to begin the survey. By clicking "Continue", you give your consent to participate in this survey.

INFORMED CONSENT INFORMATION
This informed consent document applies to final-year engineering students. The following information is provided to inform you about the research project and your participation in it. Please read this form carefully and feel free to ask any questions you may have about this study and the information given below. Your participation in this research study is voluntary. You are also free to withdraw from this study at any time.

1.Purpose of the study: The purpose of the study is to understand how well universities that offer engineering degrees are preparing their students to address development challenges in their home locales versus being trained to take newer jobs abroad. This study is being conducted in partial fulfillment of requirements for the doctoral degree. You are being asked to participate in a research study because your perspective as a member of these engineering programs is valuable, giving a first-hand account of this preparation process.

2.Procedures and duration: This study takes place over the course of 1 month. The survey takes approximately 20 minutes.

3.Description of the discomforts, inconveniences, and/or risks that can be reasonably expected as a result of participation in this study: Survey of approximately 20 minutes.

4.Good effects that might result from this study: a) The benefits to science and humankind that might result from this study: Universities in growing economies will have a better understanding of how to tailor their programs to prepare local engineers to address local problems. b) The benefits you might get from being in this study: Students may find the subject interesting, they may feel empowered getting to talk about their own opinions of the education they are receiving, and they may be motivated to get involved making changes to their own education system. It is possible that they will not feel a direct benefit.

5.Compensation for participation: entry in a raffle for the chance to win an iPad

6.Circumstances under which the Principal Investigator may withdraw you from study participation: non-responsiveness

7.What happens if you choose to withdraw from study participation: Information already provided will be kept confidential. The information already provided will be used, but it will not be linked to the student.

8.Contact Information. If you should have any questions about this research study or possibly injury, please feel free to contact Jennifer DeBoer at 615-343-4576 or my Faculty Advisor, Stephen Heyneman at 615-322-1169. For additional information about giving consent or your rights as a participant in this study, to discuss problems, concerns, and questions, or to offer input, please feel free to contact the Vanderbilt University Institutional Review Board Office at (615) 322-2918 or toll free at (866) 224-8273.

13.Confidentiality: All efforts, within reason, will be made to keep your personal information in your research record confidential but total confidentiality cannot be guaranteed. Surveys will be anonymous. Aggregated results will be available to university leaders and policymakers. Only the researcher will have access to the individual-level data. A random number generator will give each respondent an ID. Survey responses will be collected online via a password-protected instrument. After the study is concluded, the individual-level information will be destroyed.

14.Privacy: Your information may be shared with Vanderbilt or the government, such as the Vanderbilt University Institutional Review Board, Federal Government Office for Human Research Protections, National Science Foundation, if you or someone else is in danger or if we are required to do so by law.

STATEMENT BY PERSON AGREEING TO PARTICIPATE IN THIS STUDY
I have read this informed consent document. All my questions have been answered, and I freely and voluntarily choose to participate.

Please check whether you consider the following areas "local", "global", or "in-between". *

	Local	In-between	Global
Household			
Neighborhood			
City/town			
State/province			
Nation			
Region			
Continent			
World			

IN ONE SENTENCE, please give an example of a "local" engineering problem. *

Both the words "COMMUNITY" and "LOCAL" below mean local as per the option you have chosen above.

The following questions ask for your opinion on statements about local/foreign engineers and where they work.
Please choose the number from 1 to 10 that comes the closest to your own opinion.

Engineers from this community are better suited for local engineering jobs than engineers from outside the community. *
1 2 3 4 5 6 7 8 9 10
Strongly disagree Strongly agree

It is beneficial to this community if engineers trained in my university take jobs outside the community. *
1 2 3 4 5 6 7 8 9 10
Strongly disagree Strongly agree

I think engineers trained in my university often take jobs outside the community. *
1 2 3 4 5 6 7 8 9 10
Strongly disagree Strongly agree

It is beneficial if international experts are used for engineering needs in my local community. *
1 2 3 4 5 6 7 8 9 10
Strongly disagree Strongly agree

I think engineers from abroad are often hired for jobs in my local community. *
1 2 3 4 5 6 7 8 9 10
Strongly disagree Strongly agree

I am currently AWARE of engineering AROUND THE WORLD. *
1 2 3 4 5 6 7 8 9 10
Strongly disagree Strongly agree

I am currently AWARE of engineering IN MY COMMUNITY. *
1 2 3 4 5 6 7 8 9 10
Strongly disagree Strongly agree

It is important to train local engineering students to solve local problems. *
1 2 3 4 5 6 7 8 9 10
Strongly disagree Strongly agree

On a scale from "not important" to "very important", indicate how important each of the following was in your choice to study engineering. *

1 (not important) 2 (a little important) 3 (somewhat important) 4 (very important)

Potential salary
Doing interesting work
Many job opportunities
Challenge of solving problems
Profession transferable throughout the world
Opportunities to solve global problems
Hardest major and want to prove I can do it
Parental influence
Opportunities to answer local needs
Peer influence

If another factor was at all important, please explain below.

On a scale from "almost never" to "almost always", please answer the following questions. *

1 (almost never) 2 (a little) 3 (sometimes) 4 (almost always)

I was exposed to local science applications in primary school.

I was exposed to engineering in primary school.
My teachers showed they were knowledgeable about local science/engineering applications in primary school.
I was exposed to local science applications in high school.
I was exposed to engineering in high school.
My teachers showed they were knowledgeable about local science/engineering applications in high school.

Please indicate, to the best of your knowledge, the number of official connections your university has established to local and global communities. *

1 (do not know) 2 (none) 3 (a few) 4 (some) 5 (many)

university partnerships with local businesses and industry, government, or NGOs

university partnerships with international businesses and industry, government, or NGOs

university projects with local community groups or schools

university projects with schools or groups abroad

The following questions are about components of your curriculum.
Please choose the number from 1 to 10 that comes the closest to your own opinion.

In my education, I am being prepared to address local engineering problems. *
1 2 3 4 5 6 7 8 9 10
Strongly disagree
Strongly agree

The overall training I receive is highly specialized. *
1 2 3 4 5 6 7 8 9 10
Strongly disagree
Strongly agree

My university allows me to concentrate very specifically on my field of interest. *
1 2 3 4 5 6 7 8 9 10
Strongly disagree
Strongly agree

In coursework, I am being prepared to address global engineering challenges. *
1 2 3 4 5 6 7 8 9 10
Strongly disagree
Strongly agree

On a scale from "not very effective" to "very effective", please rate the following parts of your university training. *
1 (not very effective) 2 (a little effective) 3 (somewhat effective) 4 (very effective)
mathematics courses
basic sciences courses
communications courses
professional skills courses
coverage of "global" engineering problems
hands-on engineering experience
training on "local" engineering topics
research training
coverage of local cultural issues
training to work in international environment
problem solving skills
ethics training

On a scale from "not very important" to "very important", please rate the importance of learning these skills for the job you look for. *
1 (not very important) 2 (a little important) 3 (somewhat important) 4 (very important)
mathematics courses
basic sciences courses
communications courses
professional skills courses
coverage of "global" engineering problems
hands-on engineering experience
training on "local" engineering topics
research training
coverage of local cultural issues
training to work in international environment

problem solving skills
ethics training

The following questions are about extracurricular activities.

There are extracurricular opportunities to work on international projects. *

	1	2	3	4	5	6	7	8	9	10
Strongly disagree										Strongly agree

If research or internships with local projects are available, please indicate how many you have participated in.

Please check all of the extracurricular opportunities that you participate in. *

Academic societies
Recreational clubs
Competitions
Public events (speeches, festivals)
Workshops
Apprenticeships
Sporting activities
Connections with alumni
Community service/volunteering
Entrepreneurship
Conferences
Study abroad
Student publications
Professional societies
Research assistantships
I don't have time to participate in extracurricular activities.
Other
None available

Opportunities are available to work on local engineering projects outside of class. *

1	2	3	4	5	6	7	8	9	10
Strongly disagree									Strongly agree

If study abroad programs are available, please indicate how many you have participated in.

The extracurricular activities at my university are beneficial. *

1	2	3	4	5	6	7	8	9	10
Strongly disagree									Strongly agree

The following questions ask about your teachers.
Please choose the number from 1 to 10 that comes the closest to your own opinion.

On average, my professors have been knowledgeable about LOCAL engineering issues. *

1	2	3	4	5	6	7	8	9	10
Strongly disagree									Strongly agree

On average, my professors have been knowledgeable about GLOBAL engineering problems. *

1	2	3	4	5	6	7	8	9	10
Strongly disagree									Strongly agree

My professors were good teachers. *

none
a few
some
many
all

My professors were model engineers. *

1	2	3	4	5	6	7	8	9	10
Strongly disagree									Strongly agree

The following questions ask about the physical resources at your university.

The laboratories and other physical resources provide good opportunities to learn about LOCAL engineering issues. *

1	2	3	4	5	6	7	8	9	10

Strongly disagree Strongly agree

The laboratories and other physical resources provide good opportunities to learn about GLOBAL engineering issues. *

1	2	3	4	5	6	7	8	9	10

Strongly disagree Strongly agree

Please check the areas you IDENTIFY most closely with. * (In other words, which areas do you personally feel the most connected with?)

Household
Neighborhood
City
County
State/province
Nation
Region
Continent
World

These questions ask about the job you are looking for.

Please check the areas for engineering problem(s) you are most familiar with. *

Household
Neighborhood
City
County
State/province
Nation
Region
Continent
World

On a scale from "no feeling" to "strong feeling", please indicate how strongly you feel an obligation to work in engineering locally. *

1	2	3	4	5	6	7	8	9	10

No feeling
Strong feeling

On a scale from "no feeling" to "strong feeling", please indicate how strongly you feel an obligation to work in engineering abroad. *

1	2	3	4	5	6	7	8	9	10

No feeling
Strong feeling

These questions ask about your current plans.

How many offers or potential placements have you received in the last year for jobs in another country after you graduate? *

How many offers or potential placements have you received in the last year for jobs in THIS country after you graduate? *

Please check which factors make a job in your "local" community attractive to you. *

Wages
Technology
Family
Standard of living
Job availability
Familiarity with issues
Sense of fulfillment with job
None of the above

Please check which factors make a job in this country attractive to you. *

Wages
Technology
Family
Standard of living
Job availability
Familiarity with issues
Sense of fulfillment with job
None of the above

Please check which factors make a job abroad attractive to you. *

Wages
Technology
Family
Standard of living
Job availability
Familiarity with issues
Sense of fulfillment with job
None of the above

Are you going to work in engineering as your first job when you finish university? *

1 2 3 4 5 6 7 8 9 10

Definitely not
Definitely will

Will you work in engineering in your home country at any point in your career? *

1 2 3 4 5 6 7 8 9 10

Definitely not
Definitely will

Will you work in engineering at any point in your career? *

	1	2	3	4	5	6	7	8	9	10

Definitely not
Definitely will

IF NOT, please check the reasons you will switch out of engineering.

my original reasons for choosing engineering no longer apply
other subjects are better taught/more interesting
demand low for local engineers
poor teaching, inadequate advising/help
international engineering jobs not available
not interested in it
pay for local engineers not competitive
curriculum irrelevant to pressing real-world problems

Age *

Postal code of the town where you went to high school *

Father's occupation *

Mother's occupation *

Did you receive a scholarship or other financial aid to attend university? *

Yes
No

With what religious or ethnic group do you most strongly identify? *

Sex *

University name *

Engineering program *

Year that you began your undergraduate studies *

Into what field of work are you planning to go when you graduate? *

If you would like to be entered in a drawing to win an iPad, please enter your email address.

CHAPTER V

CONCLUSIONS AND IMPLICATIONS

The Acquisition and Application of Technological Capital

In the three studies of this dissertation, I can see the development of engineering ability from the problem-solving skills of a fifteen-year-old student at the end of mandatory formal schooling, through the university-based bulk of engineering training, and through to the first foray into the workforce. I am able to come close to estimation of the causal effects of major (often expensive) educational inputs. I am able to hear from the students themselves as to what path they followed and where they will go. And, I am able to parse out the complex interaction between the home background and the formal schooling system. This dissertation studies the formation of engineers through the formal and informal, subtle, and implicit processes of the engineering education system.

As I study the core of the engineering pipeline—university training—I find that there is a great deal of variation between institutions. Universities matter for achievement. Students in highly-selective institutions with well-regarded national reputations, much more research investment, and highly-qualified teachers do better. However, the technological capital accrued to the student before college still determines whether students will learn how to apply technological knowledge once they go through university training; even among similarly-selected peers, coming from a background where students have been exposed to the utility of formal schooling (parent education) and academic norms and effort (reported study time), students in higher education are better able to make use of the same resources to learn how to apply knowledge to technical problem solving.

In addition to my in-depth look at the university engineering experience, I expand the understanding of where engineering educators should focus, providing studies that look at pre-college and post-college engineers as bookends to the more-oft-thought-of college engineer. The process to train engineers begins before university, and the decision they make to enter the field after university is hugely important for the national economy. In my investigation of one particular technological tool (computers) and the acquisition and application of this tool for pre-college engineering ability, I find that policymakers must understand the context in which students acquire problem-solving skills and in which they use technology. As I gather student perspectives from graduating engineers, I find that students, though they may be passionate about engineering, have not internalized the passion for its practice or its local application.

Implications

Contribution

Technological capital is first created by home experiences, and the capacity for students to acquire it during their formal schooling is tempered by early exposure. The tracks of formal schooling then lay a path for engineers to be formed, trying to nurture the development of relevant technical skill to support national growth. But, vital engineering manpower is often run off course; students who are not as prepared to use the most valued type of technological tools and processes may not find entrée into the next level of schooling. Or, their skills might be more rewarded in another field. I find that the systematic differences in the engineers who do and do not ultimately step into the field of practice threaten the sustained growth of their respective countries. Relevant training, support, and opportunities could ameliorate this.

My dissertation makes contributions in four areas: its focus on the contextual factors supporting or inhibiting the acquisition and use of engineering skills for certain groups of students; its use of novel data; its development of a theory of technological capital; and its concrete policy recommendations. The focus here on technological capital has implications for other fields of study. The importance of the novel information I study here highlights the need for datasets similar to those at the national level in Brazil in order to answer questions of educational effects and efficiency. And, based on my findings, I detail two major policy recommendations below.

Policy Recommendations

In order to facilitate the positive role of engineering skills in development, I recommend two broad policy shifts. The obstacles that exist in the pipeline need to be cleared, and the leaks in the piping need to be fixed. In other words, the barriers to advancement that exist for engineers from certain backgrounds need to be removed, and incentives for them to stay in the engineering sector need to be put in place.

First, barriers that exist for students from low-income or other disadvantageous backgrounds should be alleviated by targeted support in the learning environment depending on the cultural background of the student and her logistical needs. Students in the hot, noisy machine shop at the Bethel Business and Community Development Center

(BBCDC) curve a blindingly silver mirror into a parabola, destined to catch the burning rays of the sun that heat the Lesotho mountains and power a solar thermal generator (BBCDC, 2011). Participants at the center are mostly adults from this remote, rural district of the tiny country. The school caters the subjects it teaches and the experiential teaching methods it employs to practical needs of the immediate community. This is one example of a tailored, supportive engineering learning structure. In another example, Swail, Redd, and Perna (2003) describe ways in which underrepresented students in the United States can better be supported as unique individuals as they navigate the college experience.

Learning opportunities like those offered by BBCDC are tailored to the distinctive characteristics of their environment. Knowing that the home, school, and community context may predict a student's behavior and educational outcomes, educators mold learning structures around local needs. Anecdotal reports illustrate the success of such models.

Worlds away from southern Africa, across rural America, schoolchildren spend over twice the recommended time, more than sixty minutes on average (Howley, 2001), riding the school bus. Children in Grapevine, Arkansas ride the bus for as much as three hours a day. But, since 2007, the ride for students in Grapevine has become an extension of the school's learning environment. Wireless receivers needle out the roof of the bus, and students can take online courses, collaborate on writing projects, and communicate with teachers (Simon, 2008). Students see value not only in using the computers, but in how they are used. This intervention demonstrates to participating children the value in this kind and this use of technology. And, in addition, children receive support in such computer use. It becomes familiar, and they adopt this usage behavior as part of their "habitus".

Students of many ages gather in a Bangladeshi village to learn from a local female teacher in a one-room school. Students too old to enter formal public school, students from communities with no government school provided, and traditionally-excluded students (e.g., females) are given the opportunity to learn in an intense, highly-interactive environment and prepare to enter official secondary schools (BRAC, 2011). These examples of tailored, targeted opportunities break down the obstacles that might otherwise prevent underrepresented students from advancing through the pipeline. BRAC and similar interventions support access for specific groups that might otherwise select out of formal education or into a less-valuable training track.

Second, incentives need to be put in place in three areas: the use and value of technological knowledge and practice, the persistence of students through the engineering training system, and the practice of engineering. In the United States, engineering societies geared towards under-represented groups in engineering abound. The Society for Women in Engineering, the National Society of Black Engineers, the National Society of Hispanic Professional Engineers, and more target under-represented groups as their missions. They provide role models to encourage students to value technology and see themselves in their roles in the future. While the extent of professional societies in the US has provided support and an attractive environment for underrepresented engineers to stay in the pipeline, there is still a notable disparity in the access of women and minorities in the engineering workforce (NAE, 2011); an expansion of supports as well as greater attention to the barriers that still exist is necessary even here, and such targeted supports are models that could be exported elsewhere.

In Brazil, companies and NGOs offer scholarships for students from rural areas to use technology in university (e.g., Revista Fator, 2007). Though such incentives are vital to recruit under-represented groups into college engineering training, they are critically needed to recruit graduating engineers and graduating engineers from under-represented groups to support the local economy. In the labor market, the incentives to practice engineering locally do not match national need. Equity, quality, and efficiency goals could be met by targeted scholarships for low-income students from companies who can also provide internships opportunities.

Future Work

The three studies of the engineering pipeline in my dissertation are first steps. Each of them leaves room for future work, and the entire dissertation lays the ground work for a larger research agenda in the future. I discuss future steps for each paper in more detail in the respective chapters.

Overall, future work includes extending analyses in terms of data included as well as updating information. It also includes recommendations for additional methodological approaches—either complementary qualitative information or a targeted randomized trial to evaluate the causal mechanism suggested by the relationship estimated. More work needs to be done to understand the similarities and differences between the contexts represented in my studies and other locales around the world. A deeper understanding of the role and working mechanism of technological capital is crucial to equitably providing opportunities for rising generations of engineers.

Building Engineers and Societies

The engineering pipeline must be reconstructed. Rather than a leaky pipe flowing downhill, losing more and more precious cargo through a series of one-way valves and no possibility of re-entry or changing course, the engineering pipeline should be inter-connected, flexible, thoroughly supported, and attractive. Students with varying backgrounds and various interests need diverse opportunities, rather than an ever-narrowing horizon of engineering futures. To best serve the needs of national and individual development, the pipeline must acknowledge the vast variation in prior experiences that students bring along with them, the connection between this and who becomes an engineer, and the need for flexibility in how students navigate their education journey. The pipeline should be tailored to the technological capital of the student.

Figure 1 broadly illustrates the concept of a “tailored pipeline”, a re-conceptualized version of the trajectory of the engineer that recognizes the numerous paths important engineering human capital should be allowed to take today. Students may change from a vocational track to an academic one and back; they may take an extra year during formal training to gain real-world experience; or, they may exit and re-enter the profession after gaining other valuable experiences. Instead of walls, multiple entry paths (gray arrows) students may take should break through traditional barriers to persistence in engineering. Instead of allowing for students to fall through the cracks in the pipeline, supports (below pipeline) exist to target those in danger of stopping out. Targeted incentives (stars) encourage students at each step to persist to the next. This newer, more realistic concept for today's student integrates the separate worlds of background, choice mechanisms, and competing incentives and obstacles that can be observed in the antiquated pipeline (Chapter I).

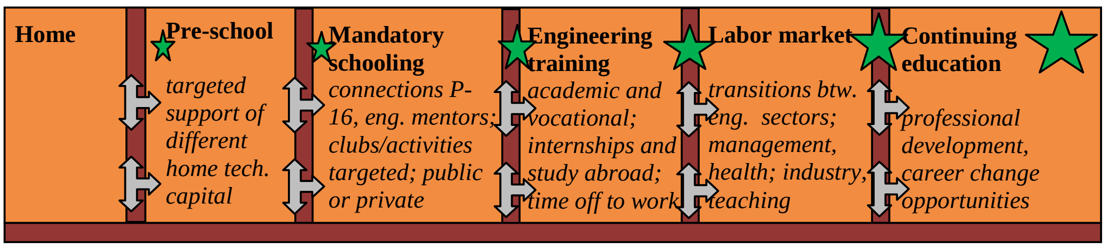

Figure 1. Reconstructing the pipeline

Improvements in schooling as we understand it are already underway. Since 1972, rural Indian women have attended Barefoot College (Barefoot College, 2011). They learn basic engineering skills, directed towards solar innovations, and they then return to their villages to implement and pass on their skills. Through this model, non-traditional students receive an education tailored to their own needs and those of their environment, and technology is both an enabler and a vital resource for this opportunity. Targeted, tailored technology use and technological training will ensure the equitable distribution of technological capital throughout a society as well as the efficient use of human capital for development.

The pathway through the engineering pipeline needs to be cleared. Only then can the infrastructure of a healthy contemporary society, the building blocks of development, the engineering pipeline pass a material test of solidity. For the starry-eyed student looking down the path towards a career as an engineer, a clear view of the night sky and an unobstructed path to a highly-valued engineering career will be possible only with policymakers' recognition of the support for engineering education that must be targeted uniquely to each individual student from an early age.

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