# Does IEB make the grade?

## Alternative testing methods and educational outcomes: The case of the IEB in South Africa

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# Abstract

According to the Independent Examinations Board (IEB, 2015), students who write the IEB National Senior Certificate school-leaving exam are at a distinct advantage and seem to be better prepared for the pressures and challenges faced during their university years than are those students who wrote the Department of Basic Education (DBE) exams. Although the underlying curriculum is no different, the IEB exam is thought to be more challenging and to encourage more critical thinking and deeper engagement with the material than the DBE exam. Thus, this research paper aims to provide a rigorous investigation of whether those students who write the IEB exam at the end of their matric year achieve higher university grades in their first year of study, as well as a decomposition of this effect into a teaching effect and a testing effect. This is done by exploiting within-school variation of examination boards. Given that studies investigating independent school impacts on university performance have predominantly been conducted internationally (McNabb et al., 2002; Ogg et al., 2009; Smith & Naylor, 2001; Smith & Naylor, 2005), this paper will add to the literature in the South African context. By using the techniques of OLS, quantile regression, binary choice probit models and ordered probit models, this paper attempts to provide a holistic view of the effect that the IEB school-leaving examination has on a student's academic performance at a tertiary level. The data used in this study is also unique, in that it is made up of an amalgamation of student record data obtained from the University of Cape Town (UCT), as well as governmental survey data. This paper finds that the IEB examination has a strong positive effect of between 1.6 and 6.5 percentage points on first-year GPA at UCT, particularly in the Medicine and Engineering faculties. Furthermore, this effect is present, but decreasing across the entirety of the performance distribution. Students with an IEB matric are significantly more likely to achieve a 2$^{nd}$ class pass or higher at the end of their first year of study than are comparable students from Former African schools. When decomposing the IEB effect into a teaching effect and a testing effect, it was found that the majority of the impact of the IEB comes simply from the different exam, and that teaching effects are minimal. A further finding of interest is that the IEB effect seems to be independent of resource availability, and that simply the exposure to the alternative testing method is sufficient for students to see significant improvements in their university performance. These results are robust to changes in functional form, and provide a strong and clear picture that perhaps South Africa should be adopting more of the IEB policies towards teaching and learning on a national scale.

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# 1. Introduction

Since its inception in the 1970s, the Mincerian wage regression has garnered support for its hypothesis that individual wages are heavily influenced by the accrual of human capital. Lemieux (2006) concludes that although it may seem old-fashioned, the Mincerian wage regression is still highly relevant today as a way of modelling income. This lends credibility to the notion that policy objectives focussed on developing educational structures may combat inequality, and as a result, the investigation of educational attainment and human capital growth should be considered an important step in order to decrease inequality and drive economic growth.

In South Africa, although the educational institutions are available, the uptake of them is poor: In 2013, only 19.7 percent (or approximately one out of every five individuals) of the population aged between 18 and 24 enrolled for tertiary education (World Bank, 2017). A similar finding by Spaull (2013) shows that out of every 100 children enrolled in primary school education, only 50 will complete Grade 12, and only 12 will qualify for university. This places South Africa far below other middle-income countries' rates of education uptake, and even though there have been policies enacted to increase participation in the tertiary education sector (Fraser & Killen, 2005), this currently still leaves the opportunity for education and wealth generation in the hands of the few.

There are three main elements posited to improve the quality of education in a country: teachers, learners and curriculum (Botha, 2002). Each of these components can be thought of as an input into why certain schooling systems perform better than others. Teachers are responsible for the dissemination of information, and depending on the quality of teachers, the quality of education can be either improved or worsened. The performance of learners is determined through a combination of their socio-economic circumstances and the tests that they write. As such, if socio-economic circumstances are held constant, different methods of testing may lead to different outcomes for learners. Finally, the curriculum can heavily influence the quality of education, as a more rigorous curriculum which is held to international standards may be considered to provide an overall better quality of education to learners.

In this paper, for otherwise identical students, differences in schooling performance are posited to depend on these three components: teaching, testing method and curriculum. The discussion surrounding the Independent Examinations Board (IEB) as a potentially superior way of preparing young South African students for tertiary education will be modelled around these three components, and a decomposition of the IEB effect on tertiary performance into each of these three components will be performed. To give context, the National Senior Certificate (NSC) is the country-wide school-leaving certificate issued in South Africa, colloquially known as the "matric certificate". The NSC can be administered by different examination boards, most prevalent of which is the Department of Basic Education (DBE).[1] The IEB is an alternative examinations board, which is offered to students attending independent schools[2] around South Africa. The underlying curriculum that is taught at an IEB school is the same as that which is taught at a standard DBE school, however, the final exams presented to DBE candidates differ from the final exams presented to an IEB candidate. Each year, Umalusi – the Council for Quality Assurance in General and Further Education and Training – conduct a standardisation of school-leaving exams across examination bodies, and they assert that the levels of the two different sets of examinations are comparable (Umalusi, 2018), however, statistical tests of the equivalence of examinations across examination boards are not readily available to the public.

The purpose of this paper, then, is to investigate to what extent the IEB school-leaving examination can benefit students in their pursuit of tertiary education, and how much of the effect accrues to the teaching effect as opposed to the testing effect. More specifically, the IEB states that they have designed a programme which aims to provide creative assessment methods that challenge the conventional methods of teaching and absorbing information (ISASA, 2019). This paper aims to investigate to what extent this approach to encouraging critical engagement with educational material can assist students in their further studies. Given that the curriculum of the IEB and the DBE schools is certified to be the same, the effect on academic performance must come down to either teaching or testing.

The hypothesis to be investigated, which is consistent with the current standpoint of the IEB, is that by enrolling for and completing an IEB matric examination, a student is better prepared for university, and as such will be able to perform better in their first year of university study, and hence be more likely to succeed in their first year at university. This paper will then further aim to back out estimates for how much of the effect can be attributed to the IEB's examination method, which aims to encourage higher-order thinking in their final assessments (IEB, 2015). This paper

1 For the purposes of this paper, to avoid verbosity, the DBE NSC examination, and the IEB NSC examination will be referred to as the DBE and IEB exams, respectively.

2 Independent schools in South Africa are what could be colloquially referred to as private schools, however, under the South African Schools Act 84 of 1996, all such schools are named as independent schools. This is then the naming convention adopted in this paper.

aims to fill the gap in the South African education literature by conducting a thorough and rigorous investigation into the impact the IEB has on university performance.

The remainder of this paper is structured as follows: Section 2 provides context of the literature on educational attainment as well as a summary of the studies that have investigated the effect of independent schools on university-level outcomes. Section 3 acts as a form of case study, providing a more detailed discussion of the South African IEB vs DBE debate. Section 4 deals with the data and method adopted in this paper, and as such is divided broadly into three subsections: The first discusses the dataset which is used in this paper, which is an amalgamation of student records data from the University of Cape Town (UCT), and governmental survey data; the second provides a preliminary look at some of the variables of interest and conducts an initial investigation of the dataset. Finally, the third subsection describes the econometric method used in this paper. Section 5 presents the results, along with a discussion of the key findings and insights, both in the case of the overall IEB effect on university outcomes, as well as the decomposition of the effect into a testing effect and a teaching effect. Section 6 concludes and offers some policy recommendations for how to consider education and curriculum development in South Africa in the future.

## 2. Educational Attainment in Context: A Review of the Global Literature

Access to, and participation in, tertiary education around the world has been an important topic of investigation for a number of years, due to its link to the theory of human capital accumulation: If individuals are able to participate in and study at institutions of higher learning, it allows for them to gain a wage premium, leading to overall economic advancement. However, as noted by Smith and Naylor (2001), the privately-borne cost of university education is rising, and this leads to fewer individuals being able to access this exceptionally valuable resource. In South Africa, specifically, the tertiary education participation rate was low – approximately 19 percent in 2014, overall (World Bank, 2018). Although Sub-Saharan Africa had lower tertiary education participation rates of 8.73 percent in 2014, the vast majority of comparable countries outperform South Africa in this regard: In particular, among BRICS nations, the country closest to South Africa is India, which still has a 6 percentage point higher participation rate than South Africa (World Bank, 2018). Policies have been put into place in order to increase South African tertiary education participation to 20 percent overall, however, since the average middle-income country had a tertiary education participation rate of 32.7 percent in 2014 (World Bank, 2018), it is clear that more needs to be done.

Although South African universities have been relatively successful in redressing inequality of access amongst previously disadvantaged demographic groups, performance at university is still of concern, with graduation rates dropping from 17 percent between 1993 and 1998 to merely 15 percent between 2000 and 2005 (Petersen et al., 2009). This suggests that it is not simply access to university that is important, but also university performance.

The determinants of university performance have been the focus of a number of studies around the world, ranging from studies on the effects of psychological factors on academic performance (see Fraser & Killen, 2005; Parker et al., 2006, for example) to those more economics-related investigations on the socio-economic and demographic determinants of university performance (see Altonji et al., 2012; Ogg et al., 2009; and Smith & Naylor, 2001, for example). This section will review these, and other, papers and their findings, providing an analysis of the methods, results and limitations of the studies conducted. This will inform the nature of the investigation carried out in this paper, which focusses specifically on the performance differential between students who wrote a state school examination and those who wrote the independent school examination. This section will begin by discussing some of the theoretical frameworks for building up a model for tertiary academic performance as well as some of the determinants found to be pertinent in explaining this performance. Thereafter, it will outline the difference between the state school examination and the independent school examination, as well as discussing the results of studies investigating the difference in university performance of students from each of these examination bodies. All the while, notice will be drawn to strengths and weaknesses of the studies conducted by other researchers, helping to inform the decisions made in this investigation.

## 2.1 The Determinants of Educational Attainment

In order to model tertiary academic performance, it is important to understand the methods and techniques employed by similar studies conducted by other researchers. Academic attainment has often been investigated at a secondary school level in South Africa, with studies being conducted on the determinants of matric pass rates or final school-leaving results (see Case & Deaton, 1999; Anderson et al, 2001; Bhorat & Oosthuizen, 2008, for example). In both these, and many other studies reviewed by Hanushek (1997) in his meta-review of this topic, the production function method of measuring educational attainment has shown great popularity. In essence, this method requires the assumption that educational attainment is some function of a number of inputs, normally considered to be factors such as individual student characteristics, teacher characteristics, parent characteristics and household characteristics, amongst others (Bhorat & Oosthuizen, 2008). Given the prevalence of this method, and its ability to assist in easily identifying and classifying factors contributing to educational attainment (Van der Berg, 2008), it is a natural choice for the model to form the basis of this study.

International studies have made use of this method to investigate academic performance at the tertiary level (Smith & Naylor, 2001; McNabb et al., 2002; Smith & Naylor, 2005; Ogg et al., 2009). While there is no South African literature dealing with this type of study directly, the variables controlled for and considerations made in past studies of South African schools may still be of use to the current study since educational attainment is cumulative, with both contemporaneous and historical factors influencing current educational attainment (Hanushek, 1997). Thus, the South African secondary school case studies can be used constructively to help broadly consider the types of variables that may influence educational attainment at the university level as well. To this end, a production function approach to educational attainment will be adopted in this paper, and the relevant covariates of interest in the models will be informed by the literature.

The first category of covariates that is considered in an educational production function is that of the individual student: These characteristics include many factors such as gender, race, as well as individual demographic and socio-economic information. To begin with, gender differences in educational attainment seem to be particularly notable in global studies. Historically, it seems that there is a gender difference in academic attainment, however, the conclusion of which gender achieves better is unclear. McNabb et al. (2002) find that although men have substantially more variation in their performance at university – a finding corroborated by Smith and Naylor (2005) – around 50 percent more men achieve first-class degrees than women. However, Smith and Naylor (2001) find that 53.4 percent of women obtained a degree of second-class or higher, while only 45.0 percent of men did the same. After an econometric analysis, they conclude that men are approximately 8.5 percentage points less likely to get a "good degree" (a degree classification of at least an upper second) than women.

It is predicted, however, that part of this gender difference in the probability of achieving a "good degree" can be ascribed to the subject of the degree, or the faculty in which the student is registered. After controlling for personal and institutional characteristics, McNabb et al. (2002) find that there are markedly different spreads of marks according to which subject an individual chose to read their degree in. The explanation presented to explain this is that perhaps more quantitative subjects are more prone to achieving extreme marks, whereas qualitative subjects are more likely to produce marks in the middle of the distribution (McNabb et al., 2002). In the case of Oxford University, Ogg et al. (2009) find that subjects such as law showed a first-class degree achievement rate of 14 percent, while mathematics showed a 39 percent achievement rate. It was noted, however, that the distinction was not simply a divide between arts and sciences, as more firsts were awarded in English than in physiology, thus suggesting the need for a more finely-divided faculty variable. Given that the University of Cape Town has six different faculties, with subjects within faculties being broadly similar, this justifies the inclusion of indicator variables for the individual student's faculty in the econometric investigation.

Interestingly, GCSE exam results seem to be better predictors of arts performance than science performance for students in the UK (Ogg et al., 2009). It was suggested that this was because arts students were more likely to be studying "joint-school" – or across two faculties – than science students: 31 percent compared to 10 percent (Ogg et al., 2009). Since the GCSE exams covered a relatively varied scope of subjects, it was argued that the GCSE exams more closely mirrored the type of degree taken by arts students, lending explanatory power to their model rather than that of science students.

Secondary school grades are used in the vast majority of tertiary educational attainment models, and are often found to be significant predictors of educational attainment at university level (Smith & Naylor, 2001; Smith & Naylor, 2005; Hazari et al., 2007; Ogg et al., 2009). According to Hanushek (1997), almost three quarters of the papers analysed in his meta-review made use of some form of standardised test score or school-leaving exam in their econometric models. The effect of higher secondary school grades varies from specification to specification, however, there is a general trend of higher secondary school results leading to higher university level achievement.

In general, secondary school grades are considered to be questionable predictors of university success (Petersen et al., 2009), however, this does not seem to dissuade the use of them in econometric models predicting university attainment. South African universities use secondary school results as a predictor of a student's success in their admissions process, as do most other tertiary institutions, however, they are supplemented by external tests such as the National Benchmarking Tests, or NBTs, in the South African case. Innate academic ability is a particularly challenging variable to control for, as the measures provided by standardised test scores are often imperfect. However, many studies use a standardised test to attempt to control for ability as this may at least mitigate some of the bias on other coefficients, even if not completely removing it (Wooldridge, 2012). Since students admitted to the University of Cape Town are required to have both written an NBT as well as complete a secondary school-leaving examination, it is possible to control for both of these in the econometric model.[3]

The NBTs, however, also present a unique opportunity to assist in decomposing the effect of the IEB effect on tertiary education. If one were to assume that differentials in academic performance depended on three factors – teaching, testing and curriculum – the NBTs provide a consistent testing method administered to all UCT students. Furthermore, the IEB and DBE curricula have been declared equivalent by the schools' governing body, Umalusi (2018). As a result, it may be possible to utilise the NBT results to isolate the pure effect of different teacher quality on university performance, given that two of the three components of performance differences can be held constant. This will be discussed further in Sections 3 and 4.3.6, below.

Even when not considering them as determinants of university grades per se, but simply as indicators of post-secondary school enrolment and completion, subjects such as mathematics, foreign languages and science are important (Altonji et al., 2012; Hazari et al., 2007). Even when controlling for the level of achievement in university level courses, an extra year of science, a foreign language and maths raise post-secondary educational attainment by 0.148, 0.325 and 0.261 years, respectively (Altonji et al., 2012). Furthermore, students opting for these more academic subject packages tend to exhibit better study habits, which may aid them in post-secondary educational attainment as well (Robbins et al., 2004). This may be of concern in the South African context, given that the number of students opting for core mathematics as opposed to the simpler mathematical literacy has dropped from 56 percent to 45 percent (Spaull, 2013). This may indicate that students enrolling in South African universities now are more at risk of underperforming at the university level than before.

School-level attainment is vastly different for different races in South Africa, with matric pass rates at Former African schools lower than those at Former White schools (Bhorat & Oosthuizen, 2008). While this is not directly linked to university-level performance, it is reasonable to assume that racial disparities which may exist at a school level will also carry through and influence

[3] While this may increase collinearity, this will simply make the estimators slightly more noisy, but will hopefully eliminate some of the potential bias present should one of these measures be excluded.

education at the university level. Of particular concern, however, is that with the lower pass rates at predominantly African schools, students from these schools will not be appropriately represented in the sample of university students. This may mean that certain students who have particularly high ability, but who did not have the resources to attend a better school will fall out of the sample, possibly skewing the underlying ability distribution. It is thus all the more pertinent to ensure that a measure of ability, such as the NBT results, is controlled for.

Family background is also an important class of variables related to socio-economic characteristics, which can impact strongly on university-level performance. In fact, there is a strong positive relationship between socio-economic background and overall university performance (Smith & Naylor, 2001; Smith & Naylor, 2005; Ogg et al., 2009). McNabb et al. (2002) found a similar result in that students who came from a professional background – i.e. where one or both parents worked as professional workers – were at a distinct academic advantage over their peers. In the same vein, there is a strong positive impact on a student's academic performance for an extra year of parent's education, whether mother or father (Smith & Naylor, 2001; Hazari et al., 2007). Furthermore, higher levels of parental education may impact on general familial attitudes towards education, and as such may assist students in adapting to university study (Robbins et al., 2004). In the case of South Africa, adults with degrees constitute only 1.6 percent of the total South African population (Van der Berg & Burger, 2003), emphasising the extreme inequality in South African society.

A further factor that may influence educational attainment at a university level is the age of the student. Mature students tend to outperform younger students, and this effect is consistent across most studies (McNabb et al., 2002; Smith & Naylor, 2005). In studying the determinants of academic performance, it is thus imperative to control for some measure of age of an individual. Smith and Naylor (2005) opt to only examine students who recently left school in their study, however, this is not exactly defined and raises a number of potential problems when trying to adapt this to the South African case: high levels of grade repetition coupled with students opting to take gap years, or who apply for mature age exemption may muddy the effect of age on academic performance.

In their study of university-level performance Smith and Naylor (2005) concluded that the effect of attending an independent school differed by school; as a result, they advocate for the inclusion of school-related variables as controls in econometric models attempting to estimate the effect of an independent school education. To this end, a number of school-level characteristics, such as the presence of a computer lab, a science lab, and sports fields, amongst others, will be included as controls in this study. This result raises the question of whether different types of schools could potentially have differing impacts on individuals' tertiary level performance. The following subsection of the literature review considers the debate at the heart of this research paper: that of the independent school premium at a tertiary education level.

## 2.2 State vs Independent Schools Internationally

While many of the factors mentioned above are important factors determining tertiary-level success, one of the factors of educational attainment which has potentially garnered the most interest from the general public is whether or not sending a child to an independent school increases their rate of success at university.  The view that students in independent schools are provided with an advantage in their tertiary studies is a view shared by McNabb et al. (2002), who predict that independent schools in England and Wales offer a higher quality of education, making it easier to adapt to university life, and thus outperform their departmental counterparts. This, however, was not the case in practice. In fact, independent schools generally underperform relative to their departmental counterparts internationally, and there are a number of studies which estimate a grade point penalty for students who have attended independent schools (Smith & Naylor, 2001; Smith & Naylor, 2005; Ogg et al., 2009; McNabb et al., 2002).

In general, these studies made use of cross-sectional data from university administrative records, and all studies have been performed in the United Kingdom (Smith & Naylor, 2001; Smith & Naylor, 2005; Ogg et al., 2009; McNabb et al., 2002). The approach utilised by these studies was to look at the probability of attaining a "good degree", and how this changed according to a number of covariates, including the student's school examination authority. The econometric model was estimated in most cases by an ordered probit model, and in one case by a multinomial logit model, with the degree classifications as the categories of the dependent variable. Smith and Naylor (2001) find that when they disaggregate the students by socio-economic class and across A-level attainment bands, the negative effect of attending an independent school is still prevalent. However, they suggest that the presence of a negative effect may not necessarily be to do with independent schools actually underpreparing their students for the tertiary education environment. Instead, they note that it is crucial to understand that when interpreting a regression coefficient, all other covariates in the regression model must be held constant (Smith & Naylor, 2001; Wooldridge, 2012). Since the model used controlled for final A-level scores, Smith and Naylor

(2001) note that when considering the negative coefficient on the independent school variable, the students they are comparing must have, in particular, the same A-level scores. Smith and Naylor (2001) argue that independent schools have a positive effect on school grades; Ogg et al. (2009) posit that this is due to independent schools being more adept at placing students in subjects in which they are likely to perform well, rather than subjects in which they will perform poorly. This effectively means that students with the same grades in independent schools and public schools are drawn from the same underlying ability distribution, but because of the independent school premium, the student from the independent school actually lies lower on the ability distribution than their public-school counterpart; their grades were simply inflated by the independent school premium (Smith & Naylor, 2001). This result, however, does not speak to whether there are differences in the examination boards administering these tests in the UK, and it seems to be that the assumption is that the final GCSE exams are all of equivalent standard, and thus, even if there are multiple exam boards, it was not of concern to the researchers. This same assumption cannot be made in the South African case, as it is clear that there are ex ante differences between the IEB and DBE examination boards that warrant further investigation.

In a further study, Smith and Naylor (2005) also provide a second explanation for this seeming independent school penalty, which hinges on socio-economic background: they argue that individuals who attend an independent school are likely to come from a family of higher socio-economic status, and as such have better outside options, should they underperform and drop out of university. As a result, students from independent schools may feel less pressure to perform well at university, and thus expound less effort in their university coursework, thus explaining the negative coefficient on the independent school variable (Smith & Naylor, 2005). In order to test this hypothesis, Smith and Naylor (2005) included an interaction term between school type and degree performance in an earnings regression. This coefficient came up insignificant, leading to a conclusion that the socio-economic status explanation was not the one driving academic performance. This stands in contrast to the results in South Africa, where socio-economic status has been shown as a key determinant of academic performance (Bhorat & Oosthuizen, 2008).

Ogg et al. (2009) posited a different hypothesis: that the negative effect of independent schools may have more to do with “teaching for the exam”, or teachers at independent schools being more likely to teach in a way that was specifically geared towards performing well in exams, but not necessarily retaining the knowledge past that point. In order to test this hypothesis, an aptitude test was run on students at Oxford University, and the results were recorded for each student, along with their GCSE (school-level) and university results. Their finding was that students from independent schools tended to underperform in their university finals relative to their GCSEs, and moreover, they underperform to a larger extent than their state-school companions (Ogg et al., 2009). However, independent school students do not underperform in their university examinations relative to their aptitude test scores. This indicates that independent school students are receiving results at university consistent with their abilities, but that their GCSE results are inflated above their ability. Furthermore, it was noted that the distribution of aptitude scores was no different for those students from independent schools and those from state schools, indicating no significant difference in underlying ability (Ogg et al., 2009). Ogg et al. (2009) argue that this is evidence of a teaching effect at independent schools, and that perhaps this effect is seen because teachers at these schools are paid directly through parents' fees, meaning that there is an incentive to place students in classes they will perform better in, and for teachers to teach towards the exam. In order to provide some clarity on this, this paper will aim to decompose the independent school effect into a teaching and testing effect, the method of which will be outlined in Section 4.3.6.

Lastly, in their 2005 study on independent school effects, Smith and Naylor discovered that the overall effect of attending an independent school on university performance was negative. However, when they disaggregated the effect and looked at the effects of smaller groups of independent schools rather than the group as a whole, they found that the variation in the size and sign of the effect was substantial: approximately half of the schools indicated a positive effect from attending an independent school, although these effects were heavily outweighed by the negative effects from the other half of schools (Smith & Naylor, 2005). Since this analysis was not carried out by the other studies investigating independent school effects, it is not possible to say whether or not there is a definite premium or penalty associated with attending an independent school. Furthermore, since all of these studies were conducted in the UK, there is no evidence pointing to what can be expected in the South African case. However, by assuming that teaching, testing and curriculum are the three main drivers of educational quality differentials, it may be that by including school-level fixed effects in a regression analysis, it will be possible to control for some form of teaching effect, while simultaneously controlling for a measure of socio-economic status. Since individual schools are likely to subscribe to a cohesive ethos, it is reasonable that the teaching ethos would be consistent within schools, and thus by controlling for school-level effects, one could potentially isolate the effect of different testing methods on university performance and isolate the effect of the IEB.

This section has aimed to provide a broad overview of the available literature focussed on estimating the effect of having attended an independent school on tertiary-level academic performance. While there is not a large body of literature focussed on this topic, there is sufficient to glean a broad idea of the methods and approaches taken to investigating this question. In an attempt to concretise this paper in the South African setting, the following section will expand on the structure of the schooling system in South Africa by presenting the differences and similarities between the IEB and the DBE as examination boards.

## 3. The IEB and the DBE: The Case of South Africa

School-leaving examinations, also known as National Senior Certificates (NSCs), in South Africa are of two main forms: the state-administered matric examination, more commonly known as the Department of Basic Education (DBE) matric exam; and the independent matric examination, administered by the Independent Examinations Board (IEB).[4] The IEB was specifically developed to maintain a non-racial examination body in South Africa following the collapse of the Joint Matriculation Board in 1989 (IEB, 2018). The Independent Schools Association of South Africa (ISASA, 2019) note that the IEB specifically aims to challenge traditional teaching and learning models by introducing new assessment methods that force critical engagement on the part of students. As it stands, schools that write the IEB examinations tend to be those which are more affluent and better resourced, and as a result, the students from IEB schools are potentially more likely to gain access to tertiary institutions.

Around the world, there has been a movement towards equalising opportunities to access higher education: Smith and Naylor (2005) note that results from school-leaving examinations in the United Kingdom are skewed in such a way that they require students from independent schools to have higher final grades to be accepted into tertiary institutions because independent school results seem to be substantially higher than state school results. These kinds of policies became particularly important to try and redress socio-economic privilege after it was noted that approximately half of the intake at Oxford University was from independent schools, although only 7 percent of all students in the UK actually attend these schools (Ogg et al., 2009).

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[4] In the South African education system, there are other examination boards, which include, for example, the Cambridge school-leaving exams. However, given that the IEB and DBE are the two main examination boards, and that the data only differentiated between DBE and IEB examinations, this paper dichotomises the education system into those two categories.

In the case of South Africa, many are under the impression that the IEB syllabus and content is more challenging than the DBE syllabus, however, this is not the case. Both the DBE and the IEB curricula are governed by the Department of Basic Education in South Africa, and the only difference between the two curricula is who ultimately sets the final school-leaving examination (IEB, 2015). Although there has been no official test to validate the equivalency of the two examination bodies, the governmental council for quality assurance in general and further education and training, Umalusi, moderates the papers and declares them to be of equal standard each year (Visser & Yeld, 2008).

However, ex ante, it would seem that there is some difference between the IEB and the DBE: As an aside to the main research question of this paper, an econometric investigation was undertaken to determine whether or not the IEB exam had an impact on school-leaving marks. A short write-up of these findings is included in Appendix A, but the key result is that there is in fact a penalty associated with writing an IEB school-leaving exam, and in fact, this penalty can be as large as 5.0 percentage points. This means that although the IEB may boast higher pass rates – 98.92% compared to the DBE's 78.2% (IEB, 2019; Department of Basic Education, 2019) – students who write the IEB exams obtain lower average school-leaving grades than their state-school counterparts, all else equal. According to the IEB (2015), there is no differential treatment of students by universities in their choice of whom to offer places to, and this could mean that IEB students are disadvantaged at the point of entry for tertiary studies.

Furthermore, according to throughput statistics, IEB students do tend to perform well at tertiary institutions, with 98 percent of ex-IEB students being enrolled in further study three years after matriculating (IEB, 2015). Similarly, between 2005 and 2007, 25 percent of first-degree recipients at the University of Cape Town were IEB students, even though these students only made up between 8 and 10 percent of the institution's intake in those years (IEB, 2015).

This immediately raises a number of questions surrounding what exactly is different about the IEB and the DBE examination bodies, and why there is a performance differential between the two examination bodies. Of course, part of this differential can be attributed to differences in socio-economic standing. Indeed, van der Berg (2008) shows that schooling systems cannot systematically overcome inherent differences in socio-economic status, and as a result, differences in socio-economic status may be instrumental in explaining differences in academic achievement. As a result, any comparison between IEB and DBE examinations has to account for differences in socio-economic status. To this end, controls for socio-economic status are included in the regression analysis, which is presented in Section 5 of this paper.

Based on the theory put forward by Botha (2002), for two students who are identical in every way except for which school they attend, one could ascribe the academic performance differential to a combination of three factors. These three components are the curriculum being taught at schools, the teachers disseminating the information, and the actual exams being written. In effect, this relationship can be stated as follows for the South African case:

$$\Delta(IEB - DBE) = f(Curriculum; Teaching; Testing) \tag{1}$$

The observed performance differential between an otherwise identical IEB and DBE student can thus be ascribed to the difference in educational philosophy embodied by these two governing bodies. In essence, then, this paper aims to investigate how an educational system which encourages greater engagement with material, and which pushes the boundaries of conventional educational norms, can have lasting effects on students' academic performance later in their lives. More specifically, in this paper, the IEB effect can be thought of as the extent to which increased critical engagement with material at a lower level can improve students' abilities to engage with more advanced content later on.

As has been asserted by Umalusi (2018) and the IEB (2015), there is no difference in the underlying curriculum being taught at an IEB school and at a DBE school. This is easily verified by examining the curriculum guidelines published by each examination body each year. By way of an illustrative example, a broad outline of the Grade 12 Mathematics curriculum is included in Table 1 below for both the IEB and the DBE.

Table 1: South African 2018 mathematics curriculum, IEB and DBE

| | IEB | DBE |
|---|---|---|
| Paper 1 topics | • Algebra and equations (and inequalities)<br>• Patterns and sequences<br>• Finance, growth and decay<br>• Functions and graphs<br>• Differential calculus<br>• Probability | • Algebra, equations and inequalities<br>• Patterns and sequences<br>• Finance, growth and decay<br>• Functions and graphs<br>• Differential calculus<br>• Probability |
| Paper 2 topics | • Statistics<br>• Analytical geometry<br>• Trigonometry<br>• Euclidean geometry and measurement | • Statistics and regression<br>• Analytical geometry<br>• Trigonometry<br>• Euclidean geometry |

Source: IEB (2018) and Department of Basic Education (2017)

As is evident from analysing the breakdown of the 2018 mathematics curriculum provided by the IEB and the DBE, the two examining bodies expect identical topics to be taught to their students. Although the mathematics curriculum is simply an example, it is possible to do such a comparison across all subjects, and the results confirm quite strongly that the curriculum across the two examining bodies is essentially identical.

It should be noted at this point that although the officially stipulated curriculum is identical for the IEB and DBE examinations, it is impossible to know whether the enacted curriculum is identical. For example, in-class assessments can take on numerous forms throughout the year, and can be set according to the teacher's discretion. These assessments could, for example, take on the form of research projects or problem sets that cover material that is not stipulated as part of the standard curriculum. However, these diversions from the prescribed curriculum are part of School Based Assessments, and have negligible effects on final subject marks, and would not feature as part of examinable material in the final exam.[5] For the purposes of this research paper, then, we

[5] According to Umalusi (2016), School Based Assessment makes up only 25% of a student's final mark for a subject. This 25% is further subdivided over a number of different assessments conducted at the school, and as such, the effect of a marginal differences in performance in one assessment will have negligible effects on overall final results.

can assume that in the case of South Africa, the curriculum across both examining boards is homogenous, and that this is not the cause of any differential in performance ascribed to the IEB. The claim then that IEB students perform better at tertiary institutions (IEB, 2015) must thus hinge on a combination of the remaining two factors: the teaching effect and the testing effect.

Given that South African universities are under substantial pressure to accept students who are likely to succeed in their studies, the IEB (2015) argues that their examinations better prepare students for success at university in the way that they test, by requiring further thought and insight in the examination answers. This is an argument which speaks towards the fact that there is a difference in testing between the two examination boards. In order to gain more insight into this, consider the following example showing the different manners in which material is tested in the Mathematics exams from November 2017.

Box 1: Excerpt from DBE Mathematics Paper 1, November 2017

**Question 6**

6.1 Mbali invested R10 000 for 3 years at an interest rate of $r$% p.a., compounded monthly. At the end of this period, she received R12 146.72. Calculate $r$, correct to ONE decimal place. (5)

6.2 Piet takes a loan from a bank to buy a car for R235 000. He agrees to repay the loan over a period of 54 months. The first instalment will be paid one month after the loan is granted. The bank charges interest at 11% p.a., compounded monthly.

6.2.1 Calculate Piet's monthly instalment. (4)

6.2.2 Calculate the total amount of interest that Piet will pay during the first year of repayment of the loan. (6)

Source: Department of Basic Education (2017)

Box 2: Excerpt from IEB Mathematics Paper 1, November 2017

**Question 3**

**Round off your answers to 2 decimal digits where necessary, unless stated otherwise.**

The owner of a Printing Company has decided to purchase machinery from China.

(a) The cost of her machinery that will be imported from China is ¥480 163 (i.e. 480 163 Chinese yuan). If the exchange rate is 1 South African rand = 0.502 Chinese yuan, calculate the total amount she will pay in South African rand. (2)

(b) The import charges amount to 5% of the value of the machinery purchased. Calculate the import charges in rand. (2)

(c) The owner intends to use her savings to purchase the machinery, which includes the import charges. She currently has R225 450 in her savings account earning interest at 9.5% effective (i.e. 9.5% per annum compounded annually). Determine **how long** it will take before she has enough money in her savings to purchase the machinery. (Assume that the price of the machinery and the import charges remains constant). (4)

(d) The owner decides that she wishes to purchase the machinery immediately. She **uses her current savings as a deposit** and approaches the bank for a loan for the balance that she requires.
The bank will offer her a loan which must be repaid at the end of each month at an interest rate of 1% per month compounded monthly over a period of 4 years.

(1) Calculate the monthly instalment. (Assume she receives the loan immediately and that the first payment is made after one month.) (4)

(2) Calculate the outstanding balance at the end of 2 years, i.e. immediately after the $24^{th}$ payment. (3)

Source: IEB (2017)

In both cases, the question presented is testing students on their knowledge of financial mathematics, and in both cases, the total marks available for the question is 15. However, the question presented by the IEB (Box 2) is more contextually dense, and as a result, less formulaic, than is the corresponding question in the DBE exam (Box 1). Although the fundamental knowledge being tested is the same in both questions – both include the manipulation of a loan which has monthly repayments, as well as the manipulation of a simple interest-bearing account – the IEB question is couched in more context than the DBE question. Furthermore, the IEB question requires some further skills to be exhibited, namely, the manipulation of exchange rates and percentages. This lends credence to the suggestion that the IEB tests in such a way that students are expected to think more critically in their answering of questions than their DBE counterparts.

The third and final component that could potentially explain the IEB-DBE performance differential is a difference in teaching quality. Ogg et al. (2009) suggest that teachers at independent schools in the UK are more qualified and hold degrees from more prestigious universities than state school teachers. This may, in turn, affect the quality of teachers, leading higher quality and more experienced teachers to move towards teaching at independent schools. If this is the case, then it is likely in South Africa that there may exist a quality differential in the average teacher from an IEB school and a DBE school, and as such, a teaching effect could play heavily into any performance differential between IEB and DBE students in standard test outcomes.

This paper will attempt to fill the gap in the South African education literature surrounding the premium accorded to IEB students in their tertiary education. By considering the case of the performance of first-year students who registered at the University of Cape Town between 2012 and 2017, this paper will begin by determining whether there is indeed an IEB premium that exists, at least in the case of UCT. This will serve as a starting point for the investigation into independent school premia or penalties in the South African case as a whole, which are particularly important given the need to redress economic inequality and inequality of opportunity that has been present in this country for many decades. The following section will give an overview of the data used in this study, by providing a brief outline of the dataset and descriptive statistics to explain the structure of the data.

# 4. Data and Method

## 4.1 Data Structure

The data used in this study is an amalgamation of a number of different datasets, namely student records data provided by the University of Cape Town (UCT) for first-year students from 2012 through to 2017; the SNAP Survey of Ordinary Schools for years 1997 to 2016[6] – a survey run by the Department of Basic Education on all schools that are not specifically geared towards vocational or special-needs students (Department of Basic Education, 2018); and the South

[6] A number of students may have taken gap years between their matric finals and their first year of university, and as a result, these students would not have been attending their alma mater school in the year before they registered at UCT. To this end, in order to obtain the most accurate reflection of the schooling infrastructure a student experienced, their matric year was matched with the SNAP Survey data corresponding to the year in which they matriculated.

African School Register of Needs Survey from 2000 – which provides data on school-level infrastructure and resource availability of all schools operating in the year 2000.

The data from UCT Student Records comprises between 4000 and 5000 individual students who registered for their first year of study at UCT every year between 2012 and 2017, resulting in a total sample of 26 301 students across the six years. Variables on students' demographic characteristics, such as race, gender, home language, parents' education levels and state grant recipient status, among others, are included, as well as variables related to schooling and academic performance. These variables include the subjects for which a student wrote school-leaving exams, their grades for these subjects, the name of their school and the year in which the student matriculated. University-level academic data includes the courses for which students registered, their marks for these courses, their home faculty and first choice of academic programme, among others. Further information in the dataset includes scores for the National Benchmarking Tests (NBTs), which are a form of standardised test, covering mathematics, English and quantitative literacy skills, stated as a prerequisite for entry into most universities, but specifically UCT; as well as residence placement, financial aid eligibility and other individual-level characteristics.

Given that the individual-level data from UCT Student Records provides a school name and province, it is possible to match students to their alma mater schools, and merge in school-level information from publicly available datasets. By matching the school name to a national education management information systems (NATEMIS) number, it was possible to merge in school-level characteristics from the SNAP Ordinary Schools Survey, and the School Register of Needs. However, due to the numerous spelling permutations that occur in the UCT student records data, this matching of some 3 000 schools had to be carried out manually. As pointed out by Bhorat and Oosthuizen (2008), the production function approach to educational attainment does not only depend on individual characteristics, but also on school-level characteristics, amongst others. Furthermore, considering that educational attainment is cumulative in nature, meaning that present educational outcomes are dependent on past educational performance (Hanushek, 1997), the inclusion of school-level characteristics is critical in estimating a true effect of the IEB matric examination on university-level academic performance. This is similar to the approach adopted by Smith and Naylor (2005), who also merged in school-level information in their investigation of the effect of independent school education on university performance in the UK.

Although this dataset covers a wide range of individual- and school-level characteristics, there are certain challenges present in the data. One of the most critical challenges facing this study is data-related. Studies conducted by Smith and Naylor (2001, 2005) and Altonji (1992) made use of a national database, which collected detailed, course-level information on academic performance for all students at all institutions across either the country or the state of interest. That this type of data is not available in a South African context limits the generalisability of the final results of the investigation. However, with UCT consistently ranked as the top university in Africa, as well as an internationally respected institution according to Times Higher Education (2018), the results of this study could potentially give an indication of how the IEB school-leaving examinations could prepare students for educational attainment on the international stage. While it would be possible to collect data from all universities around the country and merge them into a master dataset to investigate the effect of the IEB at a national level, this falls beyond the scope of this paper and is left as an avenue for further research.

A second data-related challenge is the lack of an updated Schools Register of Needs survey. The most recent iteration of this survey was completed in 2000, and as such, at the time of writing this paper, the Schools Register of Needs is nearly 20 years old. This raises a number of issues, which include the fact that schools established after the year 2000 will not be captured in the dataset, and as such, these students cannot be included in any regression analysis including school-level characteristics.[7] Furthermore, infrastructure development and resource availability at schools may have changed over time, and as such the dataset will be inaccurate and outdated.

The presence of the SNAP Survey of Ordinary Schools, however, goes some way towards mitigating the problems that arise through the lack of a more recent Schools Register of Needs survey. The SNAP survey has been carried out annually, and data up to the end of 2016 has been made available on variables such as class sizes, educator employment, and as a result, the pupil-teacher ratio, number of desks per learner and the number of boards per teacher at all ordinary schools. Thus, for many of the school-level characteristics utilised in this analysis, up-to-date data could be matched to students' information, while it is only really the quality, availability, and quantity of larger infrastructure, such as libraries, computer and science labs, and permanent buildings which rely on the data from the 2000 Schools Register of Needs. This substantially decreases the number of observations suffering from missing school-level data.

[7] A brief overview of the data shows that 30% of observations would be affected by this lack of data.

Thus, while the data available may not allow for the generalisation of results generated in this study to the national level, there is still a wealth of knowledge that can be gained by using it in an econometric investigation. The following subsection of the paper conducts a more detailed data analysis, presenting descriptive statistics and a preliminary investigation of the variables of interest to this study.

### 4.2 Preliminary Data Analysis

This section of the paper aims to give a preliminary overview of the dataset being used in this investigation, by providing summary statistics and distributional characteristics of certain pertinent variables in the dataset, as well as through graphical analysis. Given the construction of this dataset through the use of multiple different sources, as well as the confidential nature of student records data, this section is imperative in understanding the structure and scope of the dataset used in this study.

Table 2: Descriptive statistics for testing outcome

| | N | Mean | S.D. | Median | 10th Percentile | 90th Percentile |
|---|---|---|---|---|---|---|
| IEB | 4809 | 0.23 | 0.42 | 0.00 | 0.00 | 1.00 |
| Uni GPA | 25878 | 60.39 | 13.48 | 62.13 | 43.50 | 75.21 |
| Matric average | 22611 | 77.36 | 8.31 | 77.88 | 67.14 | 87.38 |
| **NBT Results** | | | | | | |
| Maths | 19079 | 59.80 | 18.27 | 59.00 | 35.00 | 85.00 |
| Academic Literacy | 22933 | 69.84 | 11.30 | 72.00 | 53.00 | 83.00 |
| Quantitative Literacy | 22935 | 64.60 | 16.33 | 65.00 | 42.00 | 86.00 |

Source: UCT student records data (2018)

Table 2 shows that the outcome variable of interest, university GPA, ranges across almost the entire scale of possible GPA values, with an average of approximately 60 percent. A potential concern is raised by the observation which indicates a university GPA of 0 percent. Given the fact that university GPA was created by averaging the marks of all courses that a particular student took in a given year, it is highly unlikely that a student would obtain an average mark of 0 percent. However, through further investigation, it was found that there was only one such student and that they truly did obtain 0 percent for one of their subjects. Furthermore, the next lowest GPA values were clustered around approximately 1.3 percent, and as such, this observation does not appear to be an outlier.

By considering the prevalence of IEB students in the sample, one can see that approximately 23 percent of first-year students at the University of Cape Town between 2012 and 2017 held an IEB matric certificate. This is approximately in line with the study conducted by Visser and Yeld (2008), who found approximately 25 percent of their sample were ex-IEB students, although it is higher than the claim by the IEB that their students make up only 8 to 10 percent of UCT first-year intake (IEB, 2015). Just as was the case in that study, IEB students are over-represented in the sample of UCT first-year students between 2012 and 2017.

The average school-leaving mark for first-year students is 77.36 percent, however, the fact that some observations have school-leaving averages of 27 percent is worrisome – the lowest mark a student can achieve and still be permitted to pass a subject at the matric level is 30 percent (Department of Basic Education, 2013). This may be the case due to measurement error in the data, and one should ensure that these individuals are not part of the sample under analysis in the regression model, for fear of introducing bias through these outliers. Indeed, after running the regression analysis presented in section 5, one can verify that the lowest matric average included in the regression sample was above 40 percent. Thus, these observations with abnormally low school-leaving marks are not of great concern.

Another point of concern in this study is the fact that although students registering at UCT are required to write the NBT standardised test, it is not compulsory for all courses to write the Mathematics NBT. Thus, it can be seen in Table 2 that almost 4 000 students did not write the Mathematics NBT. Given that there may be a selection effect amongst students who opt not to write the Mathematics NBT, a bias is likely to be introduced if the raw NBT marks are included as they are in the regression analysis. Thus, to try and avoid this sample bias, an average NBT mark variable was constructed, which averaged the marks of all NBTs that an individual student had written, and thus allowed the inclusion of all students in the regression analysis. However, as a robustness check, the regression analysis was rerun with the NBT results entered separately, but this will be discussed further in Section 5.3.

Table *3* provides a description of the distribution of the sample across a number of categorical variables of interest. When considering the distribution of students from various schools, it is clear that the majority (49 percent) of first-year students at UCT previously attended Model C schools.[8] Furthermore, the majority of UCT students register for their first year of study in the Commerce or Humanities faculties, with the Law faculty accounting for only 2 percent of the sample. Given that the law faculty is small, particularly for undergraduate law, this is not surprising, however, it does mean that any point estimates specific to the law faculty may suffer from biases brought about through small sample sizes. Furthermore, it can be seen that African and White students both account for approximately 28 percent of the UCT first-year student body, which indicates that White students are over-represented at UCT relative to the rest of South Africa. Furthermore, the majority of first-year students (61 percent) indicate they speak English at home, with IsiXhosa speakers the second-largest linguistic group at 10 percent. Also related to household characteristics, parental education levels seem to be clustered at the top end of the distribution, with 70 percent of students' mothers and fathers having a matric qualification or higher.

[8] In Apartheid South Africa, due to the introduction of the Group Areas Act of 1950, different races had to live in different areas, as well as make use of different amenities. This included the use of different schools for different races. Thus, schools under Apartheid were classified according to race. Those schools which served white students only were referred to as Model C schools, and thus a Model C school is one which was classified as "Whites Only" under the Apartheid regime.

Table 3: Distributions for selected categorical variables of interest

| | N | Share | S.D. |
|---|---|---|---|
| **School Board** | | | |
| Model C IEB | 809 | 0.05 | 0.21 |
| Model C | 8610 | 0.49 | 0.50 |
| Former Coloured/Indian IEB | 45 | 0.00 | 0.05 |
| Former Coloured/Indian | 1007 | 0.06 | 0.23 |
| Post-Apartheid IEB school | 726 | 0.04 | 0.20 |
| Post-Apartheid school (non-IEB) | 462 | 0.03 | 0.16 |
| Independent schools[9] | 2048 | 0.12 | 0.32 |
| Former African | 3994 | 0.23 | 0.42 |
| | | | |
| **Gender** | | | |
| Female | 13917 | 0.53 | 0.50 |
| Male | 12368 | 0.47 | 0.50 |
| | | | |
| **Faculty** | | | |
| Commerce | 7946 | 0.30 | 0.46 |
| Engineering & Built Environ. | 4443 | 0.17 | 0.37 |
| Humanities | 8042 | 0.31 | 0.46 |
| Law | 526 | 0.02 | 0.14 |
| Medicine | 2552 | 0.10 | 0.30 |
| Science | 2792 | 0.11 | 0.31 |
| | | | |
| **Race** | | | |
| African | 7274 | 0.28 | 0.45 |
| Asian/Indian | 2061 | 0.08 | 0.27 |
| Coloured | 3794 | 0.14 | 0.35 |
| White | 7293 | 0.28 | 0.45 |
| International/Other | 5846 | 0.22 | 0.42 |
| | | | |
| **Home Language** | | | |
| English | 16076 | 0.61 | 0.49 |
| Afrikaans | 845 | 0.03 | 0.18 |
| English & Afrikaans | 786 | 0.03 | 0.17 |
| IsiXhosa | 2698 | 0.10 | 0.30 |
| IsiZulu | 1549 | 0.06 | 0.24 |
| Other African | 2166 | 0.08 | 0.27 |
| Other Non-African | 2181 | 0.08 | 0.28 |

[9] Independent schools which operated during Apartheid in South Africa did not discriminate according to race when admitting their students (South African Schools Act, 1996). Due to this, independent schools were classified as African schools.

| | | | |
|---|---|---|---|
| **Residence** | | | |
| Not in Res | 12643 | 0.48 | 0.50 |
| Catered | 12435 | 0.47 | 0.50 |
| Self-Catered | 1223 | 0.05 | 0.21 |
| Financial Aid | 5238 | 0.20 | 0.40 |
| | | | |
| **Mother's education** | | | |
| None | 2429 | 0.13 | 0.34 |
| Some schooling | 2924 | 0.16 | 0.37 |
| Matric or equiv. | 4335 | 0.24 | 0.43 |
| Tertiary | 8374 | 0.46 | 0.50 |
| | | | |
| **Father's education** | | | |
| None | 2190 | 0.13 | 0.34 |
| Some schooling | 2904 | 0.17 | 0.38 |
| Matric or equiv. | 3572 | 0.21 | 0.41 |
| Tertiary | 8203 | 0.49 | 0.50 |
| | | | |
| **Grandparent's education** | | | |
| None | 3552 | 0.29 | 0.46 |
| Some schooling | 2574 | 0.21 | 0.41 |
| Matric or equiv. | 1427 | 0.12 | 0.32 |
| Tertiary | 4517 | 0.37 | 0.48 |
| | | | |
| **Grants** | | | |
| CSG | 1622 | 0.09 | 0.29 |
| SOAP | 1463 | 0.08 | 0.28 |

Source: UCT student records data (2018), Department of Basic Education (2018), and Human Science Research Council (2000).

Table 4, below, provides a comparison of certain socio-economic and demographic characteristics for IEB and DBE students. The first result that is particularly striking is the difference in racial composition of ex-IEB students and ex-DBE students. In particular, White students make up 54 percent of all ex-IEB students in the sample – more than twice their incidence in the ex-DBE sample. At the same time, African students are highly under-represented in the sample for both examination boards, but more so among ex-IEB students. In fact, among ex-IEB students, there are 2.57 White students to every 1 African student, compared to 0.71 White students to every 1 African student among ex-DBE students. This skewed racial profile, and South Africa's socio-economic history, suggest that there is merit to the belief that the IEB caters more-than-proportionately to South Africa's more elite populace.

Table 4: Comparison of socio-economic variables by examination board

| | DBE Mean | IEB Mean | Ratio IEB:DBE |
|---|---|---|---|
| **Race** | | | |
| African | 0.35 | 0.21 | 0.60*** |
| Asian/Indian | 0.10 | 0.07 | 0.73*** |
| Coloured | 0.20 | 0.04 | 0.20*** |
| White | 0.25 | 0.54 | 2.19*** |
| International/Other | 0.11 | 0.14 | 1.31*** |
| **Home Language** | | | |
| English | 0.59 | 0.79 | 1.33*** |
| Afrikaans | 0.03 | 0.01 | 0.45*** |
| English & Afrikaans | 0.03 | 0.02 | 0.57*** |
| IsiXhosa | 0.13 | 0.03 | 0.21*** |
| IsiZulu | 0.07 | 0.05 | 0.76*** |
| Other African | 0.09 | 0.05 | 0.53*** |
| Other Non-African | 0.05 | 0.05 | 1.02 |
| **Residence** | | | |
| Not in Res | 0.50 | 0.28 | 0.56*** |
| Catered | 0.46 | 0.69 | 1.50*** |
| Self-Catered | 0.04 | 0.03 | 0.79** |
| **Mother's education** | | | |
| None | 0.14 | 0.08 | 0.54*** |
| Some schooling | 0.16 | 0.13 | 0.83*** |
| Matric or equiv. | 0.26 | 0.17 | 0.65*** |
| Tertiary | 0.43 | 0.62 | 1.43*** |
| **Father's education** | | | |
| None | 0.14 | 0.06 | 0.42*** |
| Some schooling | 0.17 | 0.16 | 0.93 |
| Matric or equivalent | 0.24 | 0.14 | 0.58*** |
| Tertiary | 0.45 | 0.64 | 1.43*** |
| **Grandparent's education** | | | |
| None | 0.33 | 0.16 | 0.47*** |
| Some schooling | 0.23 | 0.18 | 0.78*** |
| Matric or equiv. | 0.12 | 0.13 | 1.08 |
| Tertiary | 0.32 | 0.54 | 1.67*** |
| **Grants** | | | |
| CSG | 0.12 | 0.01 | 0.08*** |
| SOAP | 0.10 | 0.02 | 0.20*** |
| **School Level** | | | |
| Electricity | 0.99 | 1.00 | 1.01*** |
| Water | 0.99 | 1.00 | 1.01*** |
| Desks per student | 0.90 | 1.10 | 1.23*** |
| Boards per teacher | 0.94 | 0.89 | 0.95*** |
| High School | 0.72 | 0.17 | 0.23*** |
| Combined School | 0.11 | 0.52 | 4.79*** |
| Financial Aid | 0.28 | 0.06 | 0.22*** |

Source: UCT student records data (2018), Department of Basic Education (2018), and Human Science Research Council (2000).

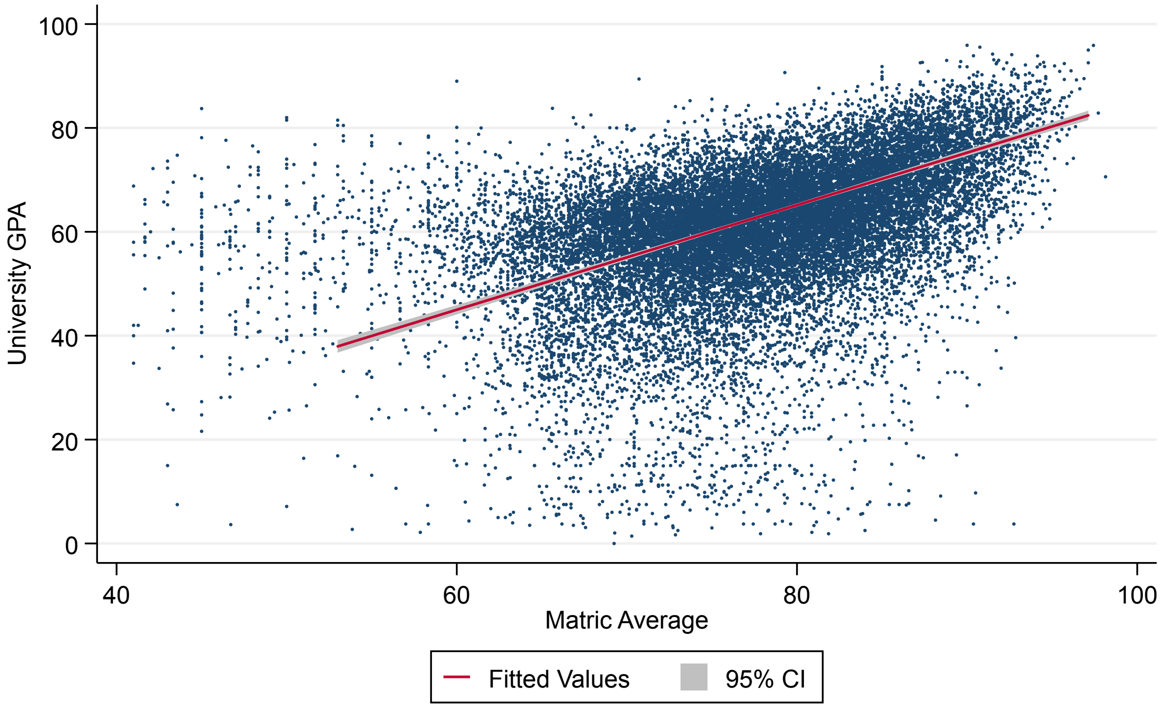
Note: *** p<0.01, ** p<0.05, * p<0.1

This result is replicated across a range of socio-economic indicators. Although proportions of students with either parent having completed tertiary education are high, these proportions are significantly higher among ex-IEB students than ex-DBE students. In fact, ex-IEB students are 43 percent more likely to have a parent with complete tertiary education than an ex-DBE student, and 67 percent more likely to have a grandparent with a complete tertiary education. Furthermore, ex-IEB students are significantly less likely to come from families that claim a Child Support Grant (approximately 12.5 times less likely) or State Old Age Pension (approximately 5 times less likely) than ex-DBE students, as well as being approximately 4.5 times less likely to be on financial aid. All of these findings suggest that ex-IEB students have significantly higher socio-economic status than ex-DBE students in the form of social and financial capital, and as a result, it is critical that these factors are controlled for when estimating how changes in the examination board can influence academic performance.

In order to understand the distribution of university results better, it would be prudent to examine the patterns and trends in the university GPA variable in more detail. In particular, to begin with, the relationship between university GPA and matric mark should be considered. In the available literature, there is divided opinion on the usefulness of school-leaving marks as a predictor of university performance. Petersen et al. (2009) note that secondary school grades are at best a questionable predictor of university-level performance; an opinion which is supported by Altonji (1992). However, other studies have found that secondary school grades are important predictors of university success, with Smith and Naylor (2001) showing that a one letter-grade mark higher per subject raises the probability of obtaining a good degree by approximately 9 percentage points. This positive relationship between secondary school results and university performance has been corroborated by numerous other studies as well (Hazari et al., 2007; Ogg et al., 2009; Robbins et al., 2004; Smith and Naylor, 2005). Given this divisive opinion regarding the importance of secondary school marks, it makes sense to investigate the relationship in the South African case.

In this dataset, there seems to be a relatively strong relationship between university GPA and matric average, as depicted in Figure 1, below. Although there is a fair amount of dispersion at the lower end of both variables, there is a rough linear trend indicating that those students whose matric averages were higher also achieve higher university GPAs. The regression coefficient from a simple linear regression of matric average on university GPA is approximately 0.69, with a t-statistic of 71.37, indicating a highly statistically significant positive relationship between the two variables. Thus, it seems reasonable to conclude that there is some form of relationship between matric average and university GPA, and as such, it will be controlled for in the regression analysis presented in Section 5.

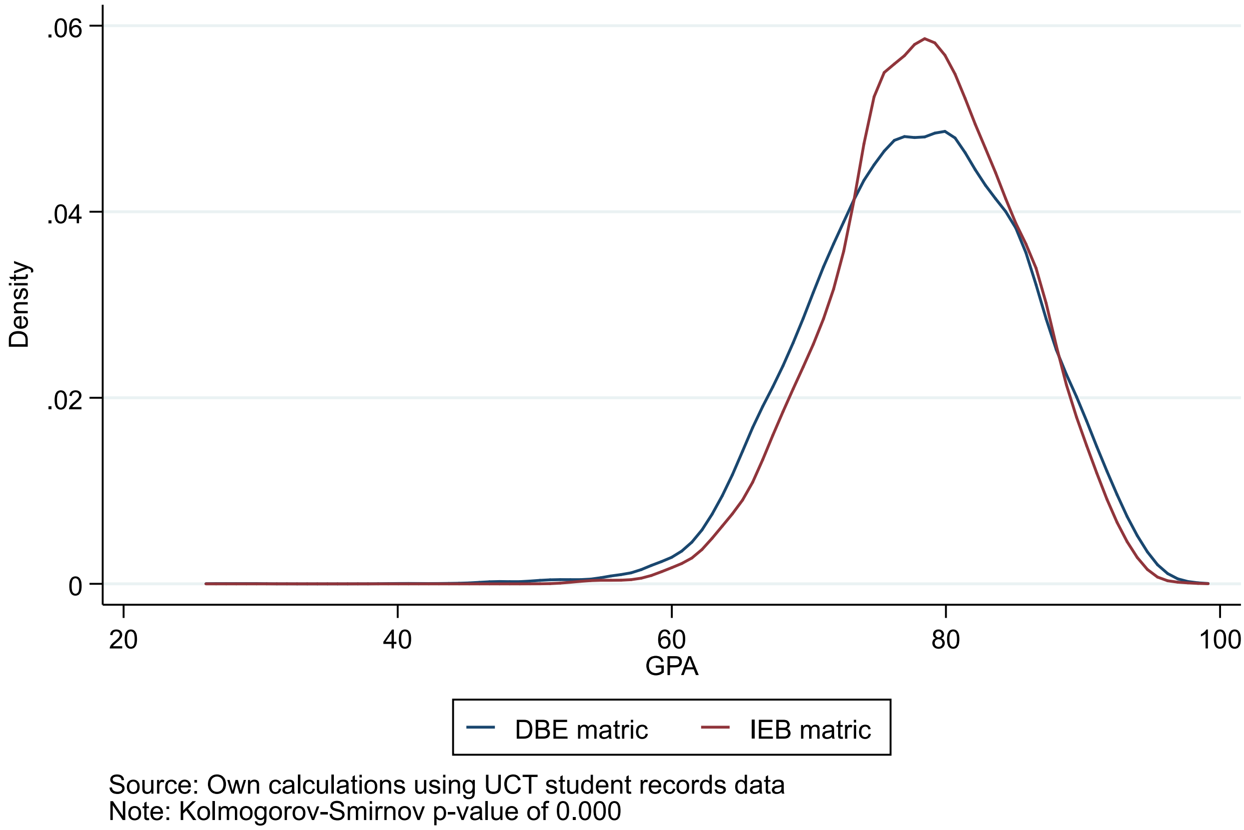
Figure 1: Correlation between university GPA and matric average, 2012 to 2017




Source: Own calculations using UCT student records data
Note: β=0.69, t=71.37

The inclusion of secondary school average as a covariate of university GPA is often to try and control for innate ability in some way, which is one of the most common unmeasurables in research on educational attainment. When considering the distribution of matric marks for IEB and DBE students, as presented in Figure 2, below, one can note that although the IEB distribution is substantially more peaked, both distributions are centred around 80 percent. It is clear that the IEB distribution lies to the right of the DBE distribution below the peak, indicating that there are fewer IEB students performing at the lower end of the spectrum of matric marks; instead, we see that there are substantially more IEB students clustered between averages of 75 and 85 percent. Statistically, when carrying out the Kolmogorov-Smirnov test for equality of distributions, the p-value returned is effectively 0, which rejects the null hypothesis of the observed distributions being equal.

Figure 2: Distribution of matric averages for UCT first-year students, 2012 to 2017



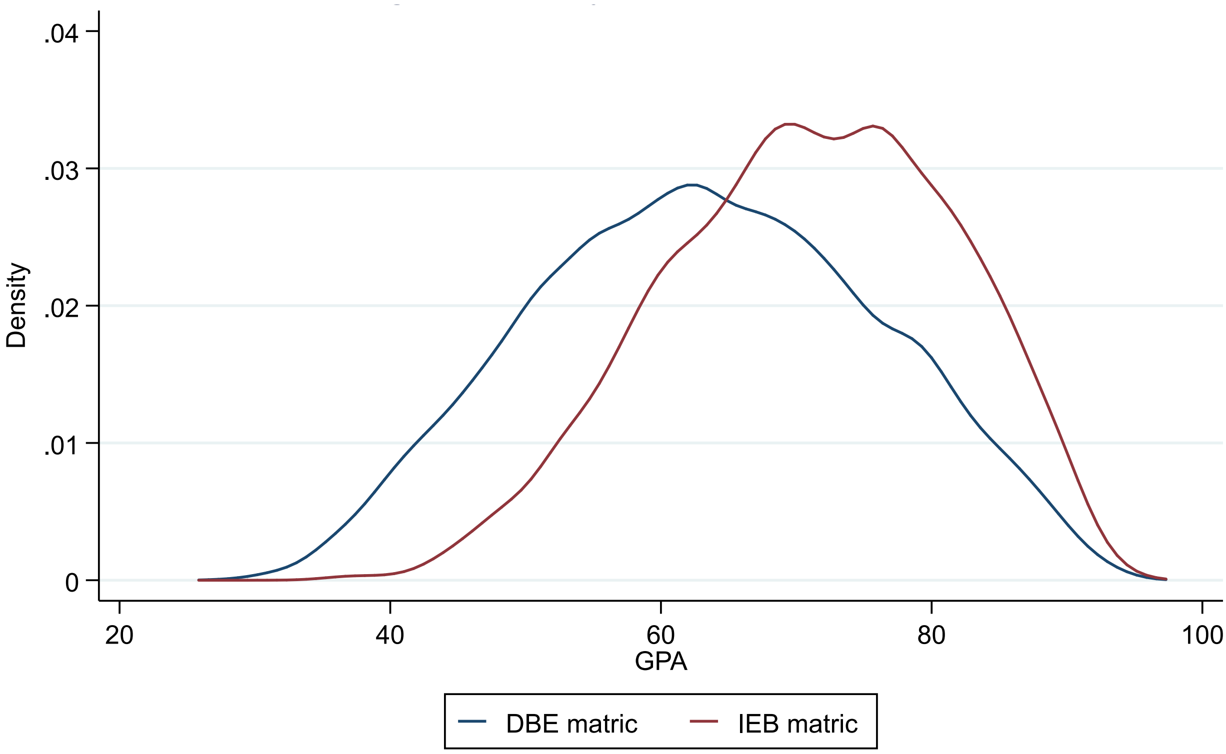

In the South African context, however, there is another potential proxy for innate ability, and one which uses a common metric for all students across the country: the National Benchmark Tests (or NBTs). The NBTs are effectively three tests administered to matric students in order to determine their academic ability – an academic literacy test, a quantitative literacy test, and an optional pure mathematics test. These three tests are administered to IEB and DBE students alike, and are a type of control test to determine the student's underlying academic ability. The distribution of mean NBT score for IEB and DBE students is presented in Figure 3, below.

The results stand in contrast to Figure 2: In Figure 3, one can see how the IEB students outperform DBE students, with the entire distribution of NBT results falling to the right of the DBE distribution. Once again, the Kolmogorov-Smirnov test rejects the null hypothesis of equality of the observed distributions. IEB students, then, seem to perform better at a standardised university-readiness test than DBE students, and moreover, this difference in performance seems to be larger than in the final matric examinations. The peak of the IEB distribution lies at close to 80 percent (which, interestingly, is approximately the IEB matric-leaving average as well), while the DBE distribution is more spread out, and has a peak at around 60 percent.

With IEB and DBE students performing at approximately the same level in their school-leaving exams, as evidenced in Figure 2, but with IEB students far outperforming DBE students in a standardised academic readiness test such as the NBTs, it raises the question of whether the matric marks are a true reflection of students' academic ability. By considering the fact that the NBTs are a standardised test, as well as the fact that the peaks of the IEB matric average and NBT distribution occur around the same mark of 80 percent, it would suggest that final matric marks should be adjusted to obtain a true reflection of academic ability. However, further rigorous investigation of this is left to further research, as it is beyond the research agenda of this paper.

What does arise from this observation, however, is the fact that there seems to be some level of performance differential between IEB and DBE students when considering a standardised test such as the NBTs. This differential in NBT performance is interesting: Given that the NBTs provide a common testing platform, and that the curriculum taught in the IEB and DBE schools are consistent, the IEB effect observed here must be attributable to some combination of the effect of socio-economic circumstance and a teaching effect. By observing this, one could use the NBTs as an intermediary tool to partial out the teaching effect in a regression analysis which controls for socio-economic standing. This would thus obtain a pure effect of the IEB testing method on academic performance. The details of this method are outlined in Section 4.3.6.

Figure 3: Distribution of mean NBT score for UCT first-year students, 2012 to 2017




Source: Own calculations using UCT student records data
Note: Kolmogorov-Smirnov p-value of 0.000

A number of studies have also found that university performance differs across faculty. McNabb et al. (2002) suggest that because of the differences in testing methods, one can expect to see more extreme results occurring in quantitative subjects, prevalent in the Science and Engineering faculties, while the Humanities faculty may produce results with less deviation overall. In fact, Ogg et al. (2009) find that there are vastly fewer first-class passes awarded to law students than to mathematics students, although they admit that the divide is not as clear as "Science versus Humanities". The University of Cape Town divides their academic programmes into six different faculties: Commerce, Engineering and the Built Environment, Humanities, Law, Medicine, and Science. Since there is a suggestion in the literature that different faculties perform at different levels, the relevant average GPA per faculty for each year from 2012 to 2017 is presented for UCT first-year students in Table 5, below. The table further includes a difference column for each year, which presents the difference in average GPA in the relevant faculty from the Commerce faculty, which was chosen as a baseline. These differences were tested to determine whether they were significantly different from 0, and the results of this test are presented in Table 5 as well.

The results show that students in the Medicine faculty consistently, and often significantly, outperform students in the Commerce faculty, sometimes by up to 5 or 7 percentage points. On the other end, however, students in the Humanities faculty often seem to significantly underperform relative to Commerce students by, on average, 4.12 percentage points. Interestingly, these results do not align with those found by van Broekhuizen et al. (2016), who note that students in Business, Commerce and Management degrees have higher completion rates than those students in Science, Engineering and Technology degrees, while having lower completion rates than those students in the Humanities and Social Sciences. It is possible that this discrepancy arises due to the fact that the metric used is different: in this case, we are concerned with first-year grades, whereas van Broekhuizen et al. (2016) are concerned with degree completion. It may be that students' academic performance adjusts over time, and as a result, first-year performance does not correlate to the rate of completion of the degree. Furthermore, this analysis is concerned only with students from the University of Cape Town, whereas van Broekhuizen et al. (2016) consider students from the 2008 national matric cohort. As a result, the UCT sample may not necessarily be representative of national trends in degree performance.

Furthermore, these results are at odds with those of Ogg et al. (2009), who investigated performance at the University of Oxford. It is, however, important to note here that comparisons between universities in different countries – in this case the University of Cape Town and the University of Oxford – are not necessarily informative. What is consistent, however, is that at Oxford university and at UCT, the performance of students in the law faculty is generally poor (Ogg et al., 2009). However, even though the results may at times be statistically significant, due to the size of the law faculty sample from UCT, these results should not be considered decisive.

Given that the faculties at UCT do show evidence of varied performance, it would be interesting to investigate whether the IEB examinations have differing effects depending on the faculty in which a student is housed. However, given that there may potentially be a sample size problem in faculties such as the Law faculty, it may be useful to cross-tabulate the detailed school classification variable discussed above and faculty of study, in order to determine whether the effect of the IEB school-leaving certificate can actually be estimated in each case. This cross-tabulation is presented in Table 6, below, which indicates the share of students from each type of school in each faculty, as well as the total number of students registered in each faculty for the period 2012 to 2017.

Table 5: Average first-year GPA by faculty, by year

| | 2012 | | 2013 | | 2014 | | 2015 | | 2016 | | 2017 | | Total | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Mark** | **Diff.** | **Mark** | **Diff.** | **Mark** | **Diff.** | **Mark** | **Diff.** | **Mark** | **Diff.** | **Mark** | **Diff.** | **Mark** | **Diff.** |
| Commerce | 60.91 | 0.00 | 61.88 | 0.00 | 63.76 | 0.00 | 62.16 | 0.00 | 58.95 | 0.00 | 61.98 | 0.00 | 61.54 | 0.00 |
| Engineering & Built Environ. | 63.47 | 2.57*** | 62.03 | 0.15 | 63.02 | -0.74 | 62.22 | 0.06 | 60.94 | 1.99*** | 59.48 | -2.49*** | 61.76 | 0.22 |
| Humanities | 57.45 | -3.46*** | 57.75 | -4.14*** | 58.75 | -5.01*** | 59.59 | -2.57*** | 55.51 | -3.44*** | 55.61 | -6.36*** | 57.64 | -4.12*** |
| Law | 56.54 | -4.37*** | 59.39 | -2.50 | 58.33 | -5.42*** | 59.84 | -2.32* | 58.45 | -0.50 | 58.96 | -3.02* | 54.74 | -2.90*** |
| Medicine | 65.96 | 5.05*** | 63.33 | 1.45* | 64.93 | 1.17* | 65.22 | 3.06*** | 66.76 | 7.81*** | 63.13 | 1.16 | 58.1 | 3.36*** |
| Science | 58.39 | -2.52*** | 59.58 | -2.30*** | 61.27 | -2.49*** | 61.85 | -0.32 | 59.06 | 0.11 | 58.52 | -3.46*** | 56.25 | -1.85*** |

Source: UCT student records data (2018)
Note: *** p<0.01, ** p<0.05, * p<0.1

Table 6: Sample distribution by faculty and school classification, 2012 to 2017

| | **Commerce** | **Engineering** | **Humanities** | **Law** | **Medicine** | **Science** | **Total** |
|---|---|---|---|---|---|---|---|
| Model C IEB | 5.16 | 4.49 | 4.37 | 6.78 | 4.20 | 3.60 | 4.57 |
| Model C | 45.41 | 47.93 | 55.30 | 49.85 | 46.97 | 42.45 | 48.64 |
| Former Coloured/Indian IEB | 0.38 | 0.34 | 0.17 | 0.00 | 0.05 | 0.26 | 0.25 |
| Former Coloured/Indian | 4.41 | 4.79 | 7.18 | 7.67 | 6.25 | 5.65 | 5.69 |
| Post-Apartheid IEB school | 4.21 | 3.40 | 4.95 | 3.54 | 2.50 | 4.37 | 4.10 |
| Post Apartheid school (non-IEB) | 2.23 | 1.97 | 2.85 | 1.77 | 2.70 | 4.01 | 2.61 |
| Independent schools | 14.37 | 11.49 | 10.99 | 10.91 | 8.85 | 8.48 | 11.57 |
| Former African | 23.83 | 25.59 | 14.17 | 19.47 | 28.46 | 31.19 | 22.56 |
| | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| Total number of students | 5325 | 2942 | 5150 | 339 | 1999 | 1946 | 17701 |

Source: UCT student records data (2018), Department of Basic Education (2018), and Human Science Research Council (2000)

As can be seen from Table 6, 48.64 percent of students at UCT hail from Model C non-IEB schools, making up a large majority of the student body. Former African schools make up the next largest proportion of the UCT student body at 22.56 percent of students, with this share even higher in the Science and Medicine faculties. The share of students from Former Coloured/Indian schools which have since become IEB-writing schools is particularly small across all faculties. Although this could allow for the estimation of an effect in this category, it may be extreme and not particularly robust. Thus, it may be worthwhile to interpret the effects obtained in the regression analysis with caution where Former Coloured/Indian schools are concerned. In general, though, there seem to be sufficient observations in the remainder of the categories to reasonably estimate the effects on students' GPA of attending schools in each category.

While university GPA has been seen to vary across a number of covariates, consistent with the literature, the key question of interest in this paper is whether there exists a premium for students who wrote the IEB examination as opposed to the DBE examination. Given the claims put forward by the IEB, one would expect that IEB students would perform better at university (IEB, 2015). Table 7, below, gives a rough indication of the premium available to IEB students across a number of demographic characteristics, which have been identified as important covariates explaining university performance.

Table 7: Average university GPA for DBE and IEB schools for all years combined, 2012 to 2017

| | DBE | IEB | IEB-DBE Difference | Ratio IEB:DBE |
|---|---|---|---|---|
| **Total** | 59.87 | 63.62 | 3.75 | 1.06*** |
| | | | | |
| **Gender** | | | | |
| Female | 60.26 | 63.42 | 3.17 | 1.05*** |
| Male | 59.43 | 63.87 | 4.44 | 1.07*** |
| | | | | |
| **Faculty** | | | | |
| Commerce | 61.43 | 65.16 | 3.73 | 1.06*** |
| Engineering & Built Environ. | 60.70 | 63.83 | 3.13 | 1.05*** |
| Humanities | 56.65 | 60.00 | 3.34 | 1.06*** |
| Law | 57.77 | 57.17 | -0.60 | 0.99 |
| Medicine | 64.29 | 69.42 | 5.14 | 1.08*** |
| Science | 58.75 | 64.70 | 5.95 | 1.10*** |
| | | | | |
| **Race** | | | | |
| African | 57.20 | 58.54 | 1.34 | 1.02*** |
| Indian/Asian | 61.23 | 62.14 | 0.91 | 1.01 |
| Coloured | 57.82 | 61.04 | 3.22 | 1.06*** |
| White | 65.10 | 66.42 | 1.32 | 1.02*** |
| International/Other | 59.16 | 61.87 | 2.71 | 1.05*** |
| | | | | |
| **Home Language** | | | | |
| English | 61.52 | 64.73 | 3.20 | 1.05*** |
| Afrikaans | 61.45 | 66.36 | 4.91 | 1.08*** |
| English & Afrikaans | 58.25 | 64.33 | 6.08 | 1.10*** |
| IsiXhosa | 55.00 | 56.02 | 1.01 | 1.02 |
| IsiZulu | 57.70 | 56.41 | -1.29 | 0.98 |
| Other African | 58.28 | 59.75 | 1.47 | 1.03** |
| Other Non-African | 59.80 | 61.23 | 1.43 | 1.02 |
| | | | | |
| **Residence** | | | | |
| Not in Res | 60.12 | 62.28 | 2.16 | 1.04*** |
| Catered | 60.13 | 64.41 | 4.29 | 1.07*** |
| Self-Catered | 54.16 | 58.30 | 4.14 | 1.08*** |
| | | | | |
| **Former Classification** | | | | |
| Former White | 61.42 | 63.69 | 2.28 | 1.04*** |
| Former Coloured | 57.12 | 66.02 | 8.90 | 1.16*** |
| Former African | 58.09 | 63.02 | 4.93 | 1.08*** |
| New Schools | 57.27 | 64.12 | 6.85 | 1.12*** |

| | | | | |
|---|---|---|---|---|
| **Year** | | | | |
| 2012 | 59.98 | 62.95 | 2.97 | 1.05*** |
| 2013 | 60.22 | 64.33 | 4.11 | 1.07*** |
| 2014 | 61.07 | 65.27 | 4.20 | 1.07*** |
| 2015 | 60.55 | 63.96 | 3.41 | 1.06*** |
| 2016 | 59.31 | 62.29 | 2.98 | 1.05*** |
| 2017 | 58.32 | 63.05 | 4.73 | 1.08*** |
| | | | | |
| Financial Aid | 58.04 | 62.72 | 4.68 | 1.08*** |

Source: UCT student records data (2018), Department of Basic Education (2018), and Human Science Research Council (2000).
Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Each line of Table 7 provides the average GPA for students who wrote the DBE exam and the IEB exam, within a particular demographic or socio-economic group. The third column presents the raw difference between the GPA averages for IEB students and DBE students, while the fourth column presents this difference as a ratio of IEB students' average GPA to DBE students' average GPA. The superscripts in the final column are indicative of a t test conducted on the equality of the means across the two groups.[10] To begin, it is clear that the IEB premium seems to exist across almost all demographic or socio-economic groups, and in most cases it is both statistically and practically significant.

The effect of the IEB school-leaving exam seems to be slightly larger for males, who achieve a 4.44 percentage point increase in GPA compared to females' 3.16 percentage point premium. Furthermore, students in the Commerce, Science, Engineering and Medicine faculties experience a substantial premium from writing an IEB exam: On average, there is a 4.49 percentage point premium to the IEB examinations in these faculties. In contrast, students in the Humanities and Law faculties see, on average, only a 1.38 percentage point premium from the IEB exam. In fact, ex-IEB students in the law faculty seem to perform worse than their DBE counterparts, although this effect is statistically insignificant and small in magnitude.

The IEB premium is present across all races of students, although for Indian/Asian students the effect is insignificant. Interestingly, however, it seems that the positive effect of an IEB matric

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[10] In this particular case, a dummy for a student having written an IEB school-leaving exam was used in place of the more detailed breakdown of school classification. This is simply for ease of comparison, however, the more detailed classifications will be used in the regression analysis presented in Section 5.

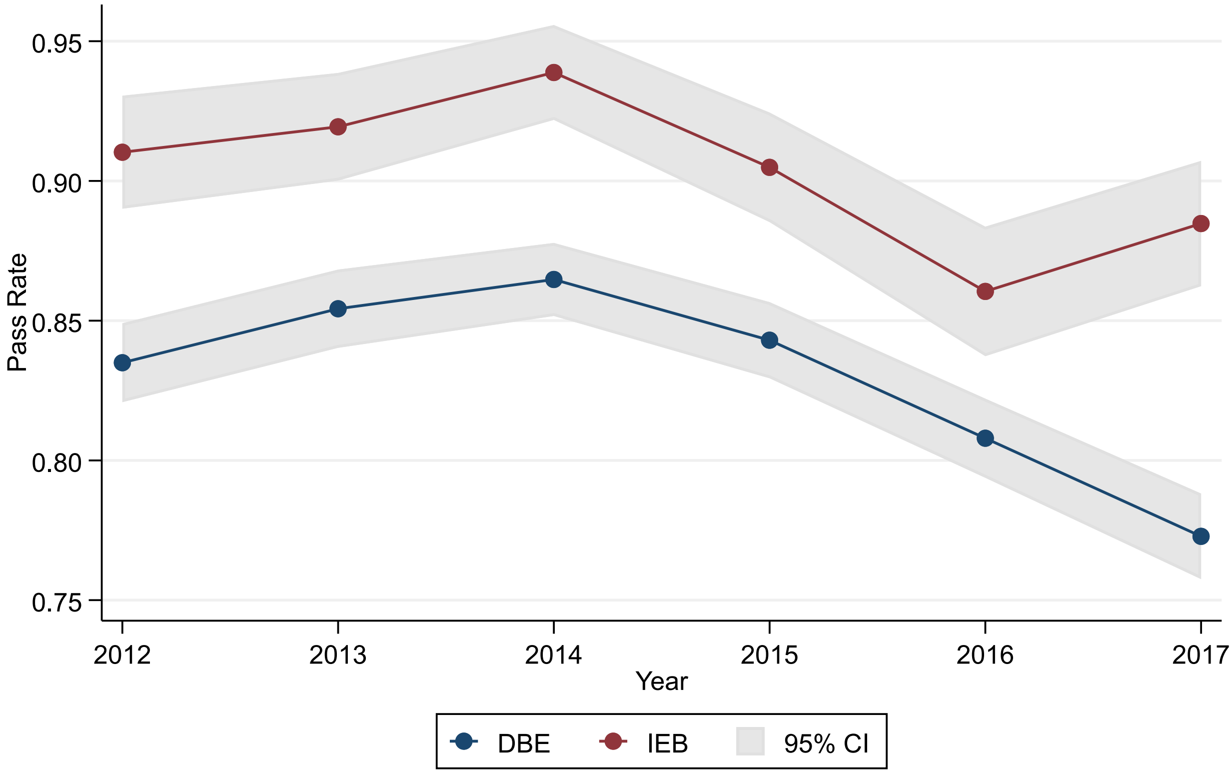
certificate is concentrated amongst those who speak either English or Afrikaans as their home language, which are also the two main languages in which the IEB examines students (IEB, 2018). This effect also seems to be persistent – and growing – over time, with ex-IEB students in 2012 achieving a 2.97 percentage point higher GPA on average than their DBE counterparts, with the premium growing to 4.73 percentage points in 2017. Given this development of the IEB premium over time, it may be interesting to investigate how the effect of the IEB exam for specific demographic and socio-economic classes of individuals developed over time. To this end, Table 7 is recreated for each year from 2012 to 2017, and presented as Table 15 in Appendix B.

While it is interesting to see the effect of the IEB school-leaving exam on GPA, all of the average GPAs depicted in Table 7 were above 50 percent, which indicates that while writing the IEB exams levies benefits on students, it is unclear whether the difference the IEB makes is material in terms of university success or not. To this end, it may be useful to consider the effect on pass rates that the IEB examination has – in other words, whether or not writing the IEB examination helps those students who are borderline cases, and could potentially move them from failing their first year to passing it. Figure 4, below, plots out the pass rates for IEB and DBE students from 2012 to 2017.

Figure 4 shows that the IEB exam does seem to increase the probability of first-year success at university by increasing the pass rate of students who write the IEB exams. This effect is statistically significant across all years under investigation. Furthermore, in 2017, during the #FeesMustFall[11] protests, ex-IEB students actually saw improved first-year pass rates, while DBE students continued to see decreasing pass rates. It should also be noted that while these pass rates are calculated on the population of UCT first-year students for each year, the confidence intervals allow for a potential inference of the pass rates at other South African universities based on the UCT sample.

[11] The #FeesMustFall protests are a movement in South Africa which aim to draw awareness to the exceptionally high cost of higher education in South Africa. Driven mainly by students, these protests have disrupted universities around the November exam block in order to force action on the part of the institution to support students who are struggling financially with the burden of tertiary education fees, and to engage critically on the decolonization of aspects of the higher education system.

Figure 4: First-year pass rates for IEB and DBE students, 2012 to 2017




Source: Own calculations using UCT student records data

In order to get a more detailed understanding of the effect of the IEB school-leaving examination on students' first-year pass rates, the average pass rate for students across various demographic and socio-economic groupings is presented in Table 8, below. Just as in Table 7, each row of the table shows the pass rate for DBE students and IEB students of a particular socio-economic group, and the final column presents the results of a t-test of equality of the two means.

Once again, the premium for ex-IEB students can be seen quite clearly: students who wrote IEB school-leaving exams are significantly more likely to pass their first year of university study at UCT than are their DBE counterparts. Pass rates are generally high, no matter which school-leaving exam is being written. Although beyond the scope of this paper, it would be interesting to investigate whether the rate of degree throughput differs for DBE and IEB students, as there may be significant differences in success rates if the measure of success is the acquisition of a degree, as opposed to passing one's first year of studies.

Table 8: First-year pass rates of DBE and IEB students compared, 2012 to 2017

| | DBE | IEB | IEB-DBE Difference | Ratio IEB:DBE |
|---|---|---|---|---|
| **Gender** | | | | |
| Female | 0.84 | 0.91 | 0.06 | 1.07*** |
| Male | 0.81 | 0.90 | 0.09 | 1.11*** |
| | | | | |
| **Faculty** | | | | |
| Commerce | 0.86 | 0.94 | 0.08 | 1.09*** |
| Engineering & Built Environ. | 0.86 | 0.91 | 0.06 | 1.07*** |
| Humanities | 0.76 | 0.84 | 0.07 | 1.10*** |
| Law | 0.86 | 0.83 | -0.03 | 0.97 |
| Medicine | 0.92 | 0.97 | 0.05 | 1.06*** |
| Science | 0.78 | 0.89 | 0.11 | 1.14*** |
| | | | | |
| **Race** | | | | |
| African | 0.78 | 0.82 | 0.04 | 1.06*** |
| Indian/Asian | 0.85 | 0.90 | 0.04 | 1.05 |
| Coloured | 0.81 | 0.88 | 0.07 | 1.09*** |
| White | 0.92 | 0.94 | 0.02 | 1.03*** |
| International/Other | 0.79 | 0.87 | 0.07 | 1.09*** |
| | | | | |
| **Home Language** | | | | |
| English | 0.86 | 0.92 | 0.06 | 1.07*** |
| Afrikaans | 0.84 | 0.91 | 0.07 | 1.09*** |
| English & Afrikaans | 0.80 | 0.90 | 0.10 | 1.13*** |
| IsiXhosa | 0.72 | 0.77 | 0.05 | 1.07 |
| IsiZulu | 0.80 | 0.79 | -0.01 | 0.99 |
| Other African | 0.81 | 0.81 | 0.01 | 1.01* |
| Other Non-African | 0.83 | 0.88 | 0.05 | 1.06 |
| | | | | |
| **Residence** | | | | |
| Not in Res | 0.84 | 0.89 | 0.05 | 1.06*** |
| Catered | 0.83 | 0.91 | 0.08 | 1.10*** |
| Self-Catered | 0.69 | 0.82 | 0.12 | 1.18*** |
| | | | | |
| **Former Classification** | | | | |
| Former White | 0.86 | 0.92 | 0.06 | 1.07*** |
| Former Coloured | 0.79 | 0.98 | 0.19 | 1.24*** |
| Former African | 0.79 | 0.89 | 0.10 | 1.13*** |
| New Schools | 0.76 | 0.91 | 0.15 | 1.20*** |

| | | | | |
|---|---|---|---|---|
| **Year** | | | | |
| 2012 | 0.83 | 0.91 | 0.08 | 1.09*** |
| 2013 | 0.85 | 0.92 | 0.07 | 1.08*** |
| 2014 | 0.86 | 0.94 | 0.07 | 1.09*** |
| 2015 | 0.84 | 0.90 | 0.06 | 1.07*** |
| 2016 | 0.81 | 0.86 | 0.05 | 1.07*** |
| 2017 | 0.77 | 0.88 | 0.11 | 1.14*** |
| | | | | |
| Financial Aid | 0.79 | 0.91 | 0.11 | 1.14*** |

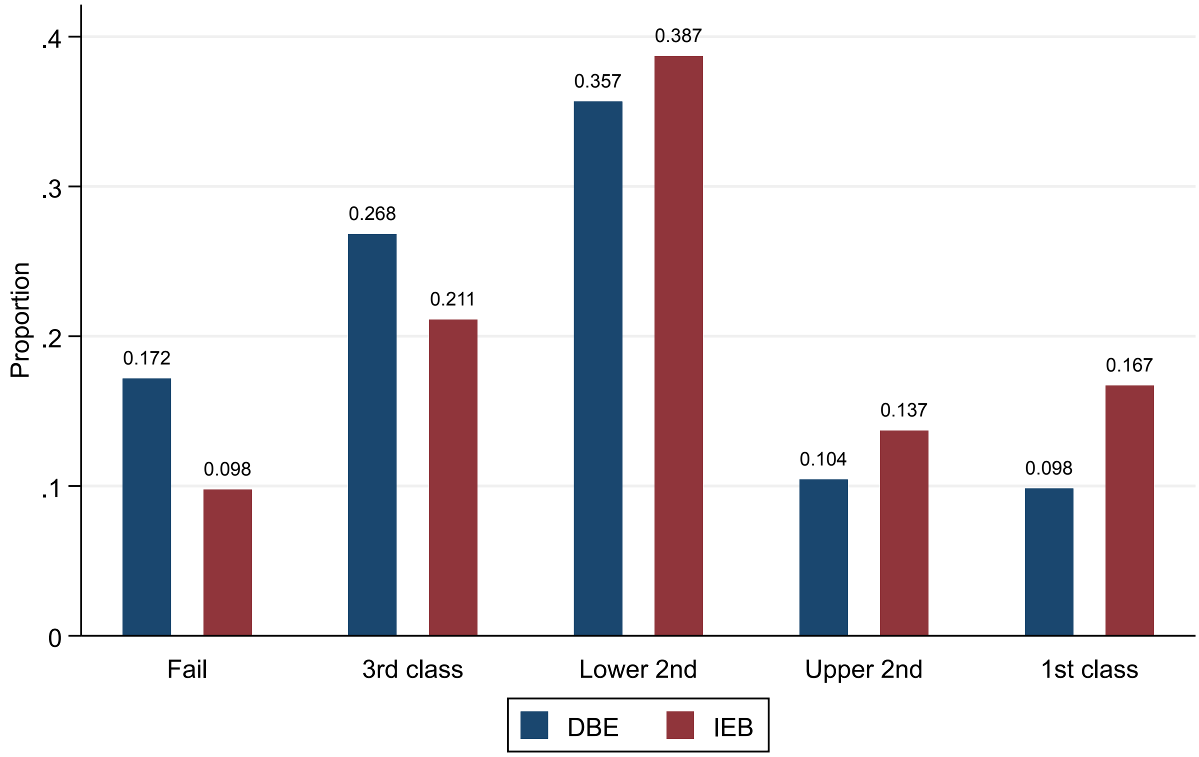
Source: UCT student records data (2018), Department of Basic Education (2018), and Human Science Research Council (2000).
Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Once again, the effects of the IEB school-leaving exam are particularly concentrated amongst those students who speak English or Afrikaans at home, and are also particularly strong for those students who are placed in self-catering residence halls. For the most part, however, similar trends can be observed in the IEB effect on pass rates as could be observed in the raw effect on GPA as presented in Table 7.

Adding further granularity to the investigation, one could also look at how the IEB school-leaving exam affects the class of pass one obtains at the end of one's first year of studies. This is a particularly popular method of investigating this research question in the UK, with many studies opting to create a dependent variable which shows the class of degree pass obtained by a student (McNabb et al., 2002; Smith & Naylor, 2001; Smith & Naylor, 2005).

Figure 5, below, indicates that in the case of UCT, students who wrote the IEB school-leaving exam are more likely to achieve at least a lower 2nd class pass (above 65 percent), and are less likely to fail or just pass their first year. Furthermore, compared to only 9.8 percent of DBE students achieving 1st class passes, nearly double the proportion of IEB students (16.7 percent) achieve a 1st class pass in their first year of study.

Figure 5: Distribution of class of pass for DBE and IEB students, 2012 to 2017




Source: Own calculations using UCT student records data

This section has provided a brief overview of the dataset being used in this research paper, as well as the characteristics of some of the key covariates of interest and how the raw results compare to those found in the local and international literature. In order to truly tease out the effect of the IEB school-leaving examination, however, one needs an econometric investigation using sophisticated statistical tools. The following section will detail the method undertaken in order to determine the *ceteris paribus* effect of the IEB school-leaving examination.

## 4.3 Econometric Method

### 4.3.1 The Production Function Approach to Educational Attainment

As stated in Section 2 which gave an overview of the global literature on this topic, the production function approach to modelling educational attainment was found to be extremely popular (Hanushek, 1997). Given its prevalence in the global literature, as well as the fact that the concept of schooling inputs being transformed into educational outputs is a relatively logical and intuitive one, this is the same method that will be adopted in this paper.

The production function approach takes the view that educational attainment is a function of a number of inputs, which can vary in number and type. The tertiary education production function in this paper uses the secondary school education production function posited by Bhorat and Oosthuizen (2008) as a starting point. The tertiary education production function posited in this paper is given by

$$Y_i = F(I_i, H_i, S_i, U_i) \tag{2}$$

where $Y_i$ is the educational attainment measure for individual $i$, $I_i$ is a vector of individual-level demographic characteristics, $H_i$ is a vector of household characteristics, $S_i$ is a vector of school-level characteristics, and $U_i$ is a vector of university-related characteristics. These university-related characteristics could include dummy variables for different universities, if the data were structured to allow such an investigation, however, in this case, this variable will include measures of university residence placement, eligibility for financial aid, and faculty of study instead. In the case of a secondary education production function, one may include teacher-level characteristics (Hanushek, 1997; Bhorat & Oosthuizen, 2008), however, at the tertiary level, information on the lecturer of specific courses at UCT was not captured, and as such cannot be controlled for.

While not without its flaws, the production function method of modelling educational attainment gives a relatively straightforward, intuitive method of conceptualising what factors should be included in a model predicting educational outcomes (Van der Berg, 2008). The shortfalls of this method, however, are that there are a number of variables which, although relevant to educational attainment, are ignored as they are not necessarily considered inputs in the production process due to their unobservable nature. Examples of some of these variables suggested by Bhorat and Oosthuizen (2008) are innate ability, or parental utility from educational investment. In an attempt to control for these particular characteristics, many studies have used a form of standardised testing to proxy for innate ability (McNabb et al., 2002; Ogg et al., 2009; Smith & Naylor, 2001), and parental levels of education to proxy for parental utility from education (Altonji, 1992; Altonji et al., 2012; Walpole, 2003). This paper will make use of similar variables, namely the NBT results of students, and parents' and grandparents' levels of education, in an attempt to control for these unobserved characteristics.

In order to model the educational production function econometrically, it is important to determine what output measure will be used to determine educational attainment. Hanushek

(1997) in his meta-review, observes that there are a wide variety of available output measures, which range from a raw percentage score to a classification of pass into different symbols from "first class" to "failure". The econometric method behind modelling the production function hinges heavily on the choice of outcome variable, as different techniques need to be applied when different measures are chosen. In this study, a range of different outcome variables are chosen in order to best describe the overall effect of an IEB school-leaving examination on first-year university performance. To this end, a number of different econometric techniques need to be applied. The remainder of this section will discuss, in detail, the econometric methods used under each choice of outcome variable.

### 4.3.2 The Method of Ordinary Least Squares

One of the most common metrics of measuring educational outcomes is to define the outcome variable as the final grade percentage a student achieves in their course of study, although this is more commonly used in elementary school-level studies (Hanushek, 1997). As a departure point for this investigation, however, opting to use first-year GPA seems reasonable, before considering other metrics to measure educational outcomes.

The simplest way to model the educational production function with final grade percentage as the dependent variable is through the use of Ordinary Least Squares regression techniques. Although one of the simplest regression techniques, OLS is a remarkably powerful tool with desirable interpretation and inference properties as long as all the relevant assumptions of the underlying population model hold (Wooldridge, 2010; Wooldridge, 2015). Modelling the educational production function using OLS provides an equation to be estimated of the form

$$\boldsymbol{Y_i} = \alpha + \boldsymbol{I_i}\boldsymbol{\beta} + \boldsymbol{H_i}\boldsymbol{\gamma} + \boldsymbol{S_i}\boldsymbol{\delta} + \boldsymbol{U_i}\boldsymbol{\theta} + \boldsymbol{Board_i}\boldsymbol{\rho} + \sum_{j=2012}^{2017} \tau_j T_j + \boldsymbol{\varepsilon_i} \qquad (3)$$

In this equation, $\alpha$ represents the constant or intercept term, while $\boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\delta}$ and $\boldsymbol{\theta}$ represent column vectors of estimated coefficients. The variables $\boldsymbol{Board_i}$ are a set of dummy variables for various school classifications, which combine the former-Apartheid racial classification as well as whether the school wrote an IEB exam or not. There are eight of these classifications, derived from four Apartheid classifications interacted with whether the school currently writes an IEB exam or not. This then implies that the coefficient vector $\boldsymbol{\rho}$ includes the partial *ceteris paribus* effect of having written an IEB school-leaving exam on a student's final mark, independent of selection effects which arise due to the type or classification of school that is available to students. Opting for this specification instead of the simple IEB-dummy specification allows one to separate the effect of the IEB matric certificate across the various school classifications. It would be naïve to believe that the IEB matric has a uniform effect no matter which school a student is from; in fact, it is more likely that schools with historically larger resource bases may see smaller effects of the IEB teaching method than would schools which were historically disadvantaged. The one disadvantage of this specification is the lack of granularity it gives in terms of decomposing the effect into a teaching and testing effect, however, this will be addressed in Section 4.3.6, later in the paper.

The terms $T_j$ for $2012 \leq j \leq 2017$ are year dummies for each year represented in the dataset, with $\tau_j$ being the corresponding coefficients, which help to model any sort of time trend picked up in the data. The term $\boldsymbol{\varepsilon_i}$ represents the idiosyncratic error term, which under the assumptions of the classical linear regression model, should be independent of all variables controlled for in $\boldsymbol{I_i}, \boldsymbol{H_i}, \boldsymbol{S_i}$, $\boldsymbol{U_i}$ and $\boldsymbol{Board_i}$, as well as being normally distributed with a mean of zero, and a constant variance, $\sigma^2$ (Wooldridge, 2010; Wooldridge, 2015).
In this paper, when defining a final percentage grade, the results for all courses taken during the student's first year of university study were weighted by the relevant credit count of each course undertaken, and the weighted average of these marks was taken as the final first-year GPA. In certain cases, however, data limitations meant that information on course grades was not directly obtainable: in the case of students being denied a Duly Performed (DP) certificate, the final mark for a course was simply recorded as "DPR", with no indication of the term mark a student had obtained throughout the course. In these cases, given that the cut-off for being awarded a DP certificate is usually a year mark of 30 percent, and examinations generally count 50 percent of a student's final mark, rather than simply ignoring these courses, any "DPR" readings were replaced with a mark of 15 percent. Furthermore, students who received an "unclassified pass", or who passed a supplementary exam were coded as having received 50 percent for the course. Students who were absent from an exam, or dropped a course, leaving it incomplete, were coded as missing, however, as there is no way to know whether the student was a top-performer who simply changed their degree path, or a student who would have failed the course. To this end, leaving these courses as missing seemed to introduce the least bias in the calculation of the final average.

The assumptions regarding the normality of the error term for OLS are particularly strong and are unlikely to hold in reality. It is possible, however, that once all the characteristics that determine academic performance have been accounted for, the disturbances from trend are simply the result of natural, or biological, shocks. This, according to Wooldridge (2015) would allow for the error term to approximate a normal distribution, and so for the purposes of this paper we assume that this is the case. Failing to assume the normality of the error term $\varepsilon_i$ will impact heavily on inference, as most commonly used test statistics, such as the t-statistic or F-statistic rely on the normality of errors in finite sample sizes (Wooldridge, 2010; Wooldridge, 2015). The large sample used in this study may allow for the test statistics calculated through the use of OLS regression techniques to be robust to slight departures from normality, and as such, allow for reasonable interpretation of economic and statistical significance, even with the assumption of normality violated (Wooldridge, 2010; Wooldridge, 2015).

In this paper, OLS regressions will be run for the population as a whole, as well as for each separate faculty in order to gain an initial understanding of how the IEB school-leaving examination may affect university performance. The inclusion of separate regressions for each faculty is justified by the literature noting significant differences in the way that school-leaving examinations affected performance in different faculties (Ogg et al., 2009).

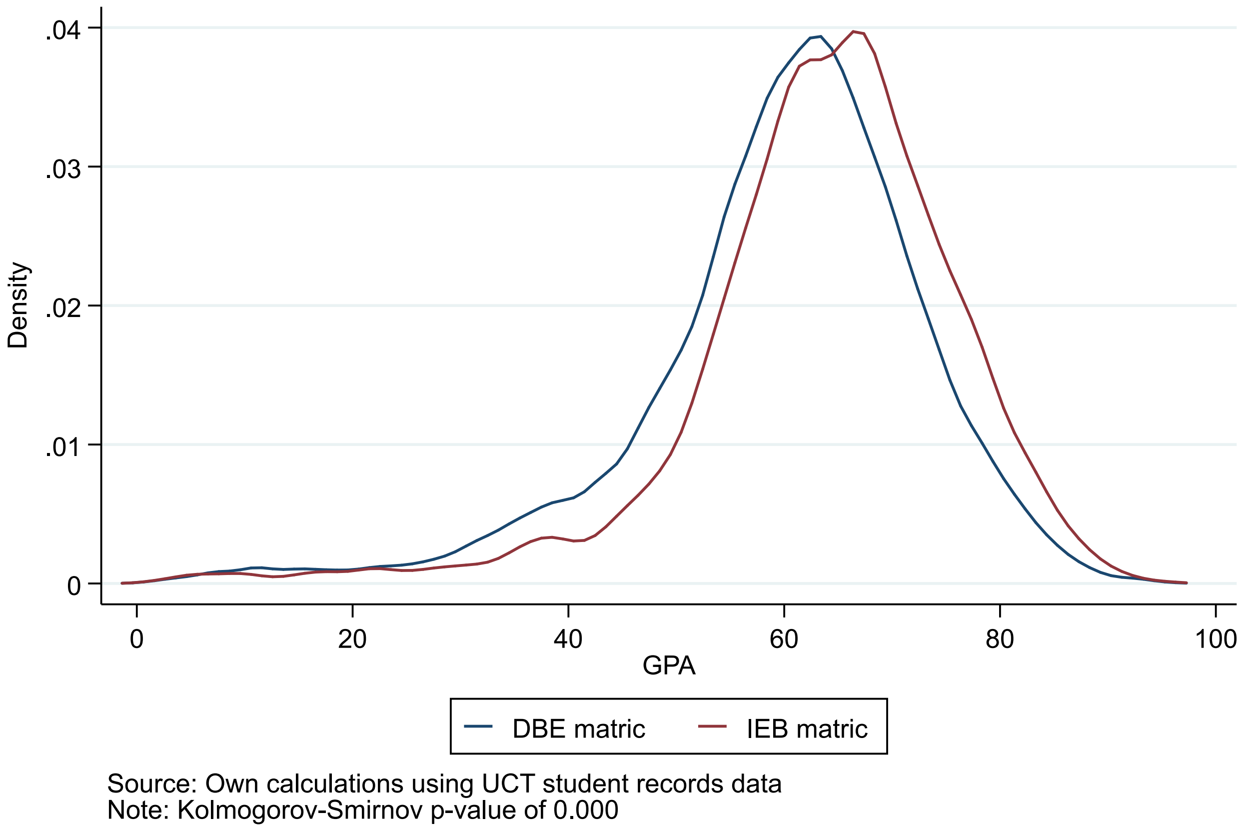
### 4.3.3 Quantile Regression Estimation

One of the criticisms levied against OLS is that while it does provide a good starting point for statistical investigation, the coefficients it provides are partial effects on the average value of the dependent variable (Gould, 1998; Wooldridge, 2010). This shortcoming of the standard OLS technique was also noted by Bhorat and Oosthuizen (2008), as well as Ven der Berg (2008). By plotting out the distribution of the dependent variable, disaggregated over the independent variable of interest, one can determine whether there is a difference in effects at different levels of the dependent variable. Bhorat and Oosthuizen (2008), in their investigation of matric pass rates, found that depending on the former Apartheid classification of schools, pass rates had vastly different behaviours. As a result of this, it became necessary to estimate quantile regressions in order to see the true effect of the independent variable of interest at each point along the distribution, rather than simply seeing the mean effect, which could obscure important variations in effect which could inform policy decisions in the future.

To this end, in this paper, I begin by estimating a kernel density of first-year university marks for the students who wrote the IEB examination, and for the students who wrote the DBE examination. The results of this are depicted in Figure 6, below. Although the distributions of university GPA seem to be relatively similar for IEB and DBE students, it is evident that the IEB distribution is further to the right than the DBE distribution. A similar pattern can be seen when considering the distributions plotted out separately for each year in the dataset. These distributions are presented in Figure 8 in Appendix B. By conducting the Kolmogorov-Smirnov test for the equality of distributions, one can easily reject the null hypothesis, and conclude that the distributions of university GPA are significantly different for IEB and DBE students.

Furthermore, there are times, particularly around a GPA of 40 percent, or at the peaks of the distributions, where the DBE and IEB distributions seem to move differently from one another, and the horizontal distance between the IEB and DBE distributions fluctuates. This is indicative of potentially different effects of the IEB school-leaving examination at different points along the distribution, which necessitates the use of quantile regressions in order to understand the full picture. The same pattern can be observed in the yearly-disaggregated distributions presented as Figure 8 in Appendix B.

Figure 6: University GPA of first-year students, 2012 to 2017




The method of quantile regression is based heavily on the method of OLS, however, where OLS only reports effects at the mean of the distribution, quantile regression analysis can report the partial effects at any specified percentile along the distribution (Gould, 1998). A particularly powerful property of quantile regressions is the notion of simultaneous quantile regression, which allows one to estimate regression equations at various percentiles along the distribution, but furthermore, one can then test cross-equation restrictions, which is impossible if the estimation of each equation was carried out separately (Gould, 1998; Wooldridge, 2010). This will allow for testing of whether the effect of an IEB school-leaving examination is constant across the entire distribution of first-year GPA or not, which is not possible with independently estimated regressions, or a single OLS regression equation.

In keeping with the precedent set by Bhorat and Oosthuizen (2008) in their use of the quantile regression method, this paper will report results for the 10th, 25th, 50th, 75th and 90th percentiles to investigate the effects of the IEB school-leaving examination across the entire distribution of first-year grades. In essence, then, this summarises into the estimation of a five-equation system of the following form:

$$\boldsymbol{Q_q}(\boldsymbol{Y}_i) = \alpha_q + \boldsymbol{I_i\beta_q} + \boldsymbol{H_i\gamma_q} + \boldsymbol{S_i\delta_q} + \boldsymbol{U_i\theta_q} + \boldsymbol{Board_i\rho_q} + \sum_{j=2012}^{2017} \tau_{q,j}T_j + \boldsymbol{\varepsilon_{q,i}} \tag{4a}$$

$$\text{where } q = 0.1, 0.25, 0.5, 0.75, 0.9 \tag{4b}$$

The coefficients and covariates in equation block (4) are defined as they were for the standard OLS estimation carried out in Section 4.2, and the values $Q_q(Y_i)$ are simply the values of the dependent variable at the $q^{th}$ quantile. The system of equations defined by equations (4a) and (4b) are then simultaneously estimated through the use of stacked OLS, and the variance-covariance matrix of the system is obtained through bootstrapping (Gould, 1998). The simultaneous estimation of the equations allows for inter-regression hypothesis testing to be conducted, allowing for checks to be conducted as to whether students across the distribution of university performance are subject to the same effect of an IEB school-leaving examination.

### 4.3.4 The Binary Choice Model – Probit Estimation

A further method of estimating the effect of the IEB school-leaving examination would be to dichotomise first-year students into those who passed their first year and those who failed it. While the standard and quantile OLS regression methods are useful for examining the effect on overall GPA, it is also important to ascertain whether the IEB examinations have a real impact on the success rate of students in tertiary education. To this end, the use of a binary choice model can assist in determining how the IEB examination can assist those students on the margin.

The use of discrete choice models in the literature is not particularly popular, possibly because studies have opted to rather investigate the impact of independent school education on degree-class through the use of ordered probit or ordered logit models (McNabb et al., 2002; Ogg et al., 2009; Smith & Naylor, 2001; Smith & Naylor, 2005). The binary choice probit or logit models are simply special cases of the ordered probit and logit models, where there are only two categories (Wooldridge, 2010), and as such, many researchers may not see the need to run both regressions.

However, some studies have included the binary choice model, such as Alon (2005) who estimated the probability of college completion for a cohort of students in Indiana, America using a probit model, or Smith and Naylor (2001) who estimated a model predicting the probability of obtaining a "good degree"[12]. Thus, there is precedent for the inclusion of a binary choice model in this paper, which can be used to examine whether the IEB school-leaving examination has any material impact on whether students pass or fail their first year of tertiary studies.

To define the binary choice model, one first has to determine whether to use the probit or logit binary choice model. A great deal of the literature opts for the probit option rather than the logit option (Alon, 2005; McNabb et al., 2002; Smith & Naylor, 2001; Smith & Naylor, 2005), with only one incidence of the choice of a logit model (Ogg et al., 2009). Ultimately, the choice of probit or logit model comes down to the error distribution in the underlying latent variable model, described as

$$Y_i^* = \alpha + \boldsymbol{I_i\beta} + \boldsymbol{H_i\gamma} + \boldsymbol{S_i\delta} + \boldsymbol{U_i\theta} + \boldsymbol{Board_i\rho} + \sum_{j=2012}^{2017} \tau_j T_j + \boldsymbol{\varepsilon_i} \qquad (5a)$$

$$Y_i = 1[Y_i^* > 0] \qquad (5b)$$

where $\boldsymbol{Y_i^*}$ is some unobserved latent variable, which depends on the independent variables defined as in equation (5a). The model described in equation (5a) should also follow the same extra assumptions as the classical linear regression model, as discussed after equation (3): namely, exogeneity of the independent variables and the idiosyncratic error, homoskedasticity and

[12] A "good degree" is defined as one where the student achieved a second-class pass or higher in their studies.

normality of the error. The value of $Y_i^*$ influences whether we observe a value of 1 or 0 for our measured dependent variable depending on where the latent variable lies in relation to a cut-off point, as described in equation (5b). In the context of the educational production function, the latent variable $Y_i^*$ is a student's first-year GPA, which will influence whether one observes a pass ($Y_i = 1$) or a fail ($Y_i = 0$).

Equation (5a) can be directly linked to equation (3), describing the OLS regression line, and as such, if the idiosyncratic error is assumed to have a normal distribution in running OLS, it should have a normal distribution in this case as well. If we accept that the $\varepsilon_i$ are normally distributed, then this necessitates the use of a probit function rather than a logit function for the estimation of the binary choice model (Wooldridge, 2010; Wooldridge, 2015).

After the estimation of the probit model is complete, the estimation of the marginal effects of the model is required for interpretation purposes. Calculating these marginal effects requires the choice between the average marginal effect (AME) or the marginal effect at the average (MEA). Given that the average values of binary independent variables are never observed in practice, and as such, the marginal effect at the average values of these variables is practically implausible, this paper opts for the AME in all cases. The AME is simply an average of the estimated marginal effects across all $n$ observations, as described in equation (6) (Wooldridge, 2015).

$$AME = n^{-1}\left[g\left(\boldsymbol{X_i}\widehat{\boldsymbol{\beta}}\right) \times \hat{\beta}_j\right] \tag{6}$$

Assuming that the latent variable model described in equation (5a) follows the assumptions of the classic linear regression model, inference should once again be possible. Recall that it was assumed that the model prescribed in equation (3) for estimation by OLS was unlikely to follow these assumptions in reality, but that through invoking the asymptotic properties of OLS, one could generate broadly acceptable test statistics. To this end, the same assumptions will apply to this model, and the test statistics used for calculating significance will be considered broadly appropriate.

### 4.3.5 The Ordered Probit Model

The estimation procedure which has received the most traction in the literature estimating university academic achievement is that of the ordered probit model (McNabb et al., 2002; Smith

& Naylor, 2001; Smith & Naylor, 2005). In these studies, the student's grade is split into a number of different categories, indicating the class of pass obtained in their degree. Due to the fact that these categories are defined according to the student's final GPA, there is a natural ordering to the categories, and as such, this provides a justification for the ordered probit model as opposed to the multinomial probit model, which does not impose an order on the categories of the outcome variable (Wooldridge, 2010).

The ordered probit model relies on a latent variable model that underlies the data-generating process, just as was the case with the binary choice probit model. This latent variable model is defined as before, however, now the outcome variable does not only vary between 0 and 1, but rather across a range of discrete outcome values according to where the underlying latent variable falls within a range of cutoff points (Wooldridge, 2010). Mathematically, the latent variable model can be expressed as follows:

$$Y_i^* = \boldsymbol{I_i\beta} + \boldsymbol{H_i\gamma} + \boldsymbol{S_i\delta} + \boldsymbol{U_i\theta} + \boldsymbol{Board_i\rho} + \sum_{j=2012}^{2017} \tau_j T_j + \boldsymbol{\varepsilon_i} \tag{7a}$$

$$Y_i = \begin{cases} 0 & if \quad Y_i^* \leq \kappa_0 \\ 1 & if \quad \kappa_0 < Y_i^* \leq \kappa_1 \\ 2 & if \quad \kappa_1 < Y_i^* \leq \kappa_2 \\ \vdots & \\ m & if \quad Y_i^* > \kappa_{m-1} \end{cases} \tag{7b}$$

The model in equation (7a) omits the constant $\alpha$ from the estimation, as the inclusion of a constant raises an identification problem: by adding any arbitrary constant to the intercept in equation (7a), as well as to every one of the cut-off points in (7b), $\kappa_0, \kappa_1, \dots, \kappa_m$, we would observe the same outcomes under a different population model (Wooldridge, 2010). Thus, it is customary to rather omit the constant from the estimation procedure, and specify the ordered probit model in this way. Also important to note is that once again, the choice of the ordered probit model makes the assumption that the idiosyncratic error term $\boldsymbol{\varepsilon_i}$ is normally distributed, rather than logisitically distributed as it would be under the ordered logit model (Wooldridge, 2010). As per the assumptions made in the sections detailing the OLS estimation, as well as the probit estimation, this paper takes the view that the error terms are likely the result of natural or biological disturbances due to unobservable individual characteristics. As such, the $\varepsilon_i$ can be assumed to be approximately normally distributed, and even if this does not hold exactly true in reality, it is at least approximately true. This then necessitates the use of the ordered probit model as opposed to the ordered logit. This is a methodological choice supported by the literature, as three out of the four studies concerned with degree classification at tertiary level made use of ordered probit models (McNabb et al., 2002; Smith & Naylor, 2001; Smith & Naylor, 2005), while only one made use of a multinomial logit model in their investigation (Ogg et al., 2009).

Equation (7b) above depicts the underlying relationship between the observed outcome variable $Y_i$ and the latent unobserved variable $Y_i^*$. As $Y_i^*$ moves across a roughly continuous range, it is classified into one of $m+1$ different categories, depending on where it falls in relation to the cut-off points $\kappa_i$. In the context of this paper, both of these outcome variables are actually observed, however, for the purposes of the ordered probit model the latent variable $Y_i^*$ is a student's final first-year GPA, while the observed variable $Y_i$ is an outcome variable classifying the class of pass achieved by the student. In keeping with the definition of pass classifications as given by UCT, this paper divides first-year GPA into five ordered categories: a first-class pass (for a GPA above 75 percent), an upper-second class pass (for a GPA between 70 and 75 percent), a lower second-class pass (for a GPA between 60 and 70 percent), a third-class pass (for a GPA between 50 and 60 percent), and failure (for a GPA below 50 percent). These are coded from 1 for a first-class pass through to 5 for a failure in this paper's estimation of the model, however, as long as the order is preserved, the actual numerical values are not of any great consequence and can be reversed or even monotonically transformed, so long as the order is preserved (Wooldridge, 2010).

Once again, in the case of the ordered probit model, the estimated coefficients are not easily interpreted, and one has to calculate marginal effects once more. Given that there are $m+1$ outcome categories, there must be $m+1$ probabilities available for estimation, and $m+1$ marginal effects. The average marginal effect will once again be the marginal effect of choice, which can be calculated using a slightly adapted version of equation (6), where the marginal effects which are averaged are simply replaced by the corresponding marginal effects for the ordered probit model. As was the case in the probit model, inference will be conducted on the estimated coefficients, however, given the error term's departure from normality, asymptotic theory will be invoked in order to ensure reasonable test statistics.

### 4.3.6 Decomposing the IEB Effect

As has been noted in Section 3, three factors may influence a performance differential between two otherwise identical students, one of whom wrote the DBE examination, and the other who wrote the IEB examination: the curriculum, a teaching effect, and a testing effect. As has also been concluded, the curriculum in question is homogenous across both examination boards, leaving the difference in students' performance dependent on either teaching effects or effects resulting from different testing methods.

The methods outlined in the previous subsections fall short in one key way: They do not isolate the part of the IEB effect which is attributable to teaching, and that which is attributable to the different testing methods. Given that this paper is particularly interested in the effect of the IEB examination on tertiary educational outcomes, it is imperative that the pure testing effect of the IEB can be extracted.

One method of obtaining this result takes inspiration from the study conducted by Smith and Naylor (2005), where the individual school that a student hailed from is controlled for in the regression analysis. This would result in a model specification as below:

$$Y_i = \boldsymbol{I_i\beta} + \boldsymbol{H_i\gamma} + \boldsymbol{S_i\delta} + \boldsymbol{U_i\theta} + \boldsymbol{Board_i\rho} + \sum_{j=2012}^{2017} \tau_j T_j + \sum \boldsymbol{School_i\chi} + \boldsymbol{\varepsilon_i} \qquad (8)$$

In this specification, the variable $\boldsymbol{School_i}$ is a dummy variable indicating which school the individual student attended, and all other variables are defined as before. This equation is estimated via OLS in this paper, however, if the dependent variable of interest were to change, one could adjust the technique according to the methods outlined earlier in this section.

The advantage of this specification is that it effectively controls for school fixed-effects, and as a result, any effects that are unique to a particular school are captured in the coefficient vector $\boldsymbol{\chi}$. Since the teachers at a particular school are unique to that school, this coefficient estimate will then capture the teaching effect, among other unobserved school-level effects. The main assumption required here, however, is that teachers from the same school all have a similar teaching effect on students' performance. Although this may not be exactly true, it seems a reasonable assumption that teachers from the same school will, in general, have a similar work ethic and ethos towards teaching their students. Thus, it seems reasonable that a school dummy variable would be able to pick up the teaching effect, assuming that teachers are of reasonable similarity in their effectiveness.

If this is the case, then the coefficient vector $\boldsymbol{\rho}$ will account for the effect of IEB schools which is not to do with curriculum (as this is constant) or teaching (which is controlled for through school dummies). In actuality, this coefficient vector $\boldsymbol{\rho}$ will capture the effect of a school changing from one examination board to another, and thus, we obtain an estimate for the pure effect of the IEB assessment or testing method on a student's tertiary academic performance.[13]

As a robustness check, one could employ a slightly different technique to estimating the effect of the difference in testing procedures between the IEB and DBE. In this case, the method put forward by Ogg et al. (2009) of comparing students' performance to an external standardised test is adopted. In the study conducted by Ogg et al. (2009), students' performance in their school-level exams was compared to their university exams and an ability test. This ability test was the same for all students, and was used as an exogenous measure of students' academic prowess.

In the South African case, an externally administered test is available in the NBTs. By utilising the NBTs as a form of ability test, one can determine whether students are over- or underperforming at university relative to their ability as measured by the NBTs. The argument put forward by Ogg et al. (2009) is that teaching effects are present if there is a relative over- or underperformance of specific school types in the aptitude test administered to students. Thus, one could determine whether a teaching effect exists in the South African case by running the following regression using OLS:

$$\boldsymbol{NBT_i} = \boldsymbol{I_i}\mathrm{B} + \boldsymbol{H_i}\Gamma + \boldsymbol{S_i}\Psi + \boldsymbol{U_i}\Theta + \boldsymbol{Board_i}\mathrm{P} + \sum_{j=2012}^{2017} \Upsilon_j T_j + \boldsymbol{e_i} \tag{9}$$

The presence of statistically significant $\mathbf{P}$ coefficients for IEB schools is then indicative of a teaching effect present at IEB schools. If one were to then make use of the residuals from this regression, $\boldsymbol{e_i}$, and insert them into the original OLS specification, as given in equation (3), then they would act as a measure of a student's ability that has been netted of any teaching effects. This then means that the school board coefficients from the original OLS regression, augmented by the residuals from equation (9), would be net of any teaching effects and as a result, produce estimates of the IEB effect which is purely the result of the different testing method.

[13] This method assumes that there are schools which switch from one examination board to the other during the period under observation. This does occur in the data, and is discussed in more detail in Section 5.2.

This subsection has detailed the econometric method undertaken to investigate the impact of an IEB school-leaving examination on first-year university academic outcomes. The use of a number of different metrics measuring academic performance necessitate the use of a number of different econometric techniques, as described above. These different techniques, although trying to answer the same broad question, bring the question of interest down to different levels of granularity, and as such, there is value to be had in including all of the above models in this investigation.

Many other papers on the topic of tertiary educational attainment opt for only one outcome variable, and as such only present estimates from one, or at most two, types of models. This paper, however, shows a vast array of different model specifications for different outcome variables, which both add to answering the research question, as well as act as robustness checks for the other models. The following section presents the results of these estimations, while also presenting a discussion of the implications of the results, as well as how they compare to other studies within the global literature.

## 5. Results

This section of the research paper presents the results of the regressions run as per the method outlined in Section 4.3. This section will begin with the presentation and discussion of the results pertaining to university GPA. This includes the OLS, quantile, probit and ordered probit regressions which aim to tease out the effect of an IEB school-leaving examination on university performance. Thereafter will follow a discussion of the decomposition of the IEB effect in order to isolate the testing effect on university performance specifically. This section will conclude with a brief discussion of the robustness checks conducted in order to ascertain the validity of the results, which may open up areas for further research which lie beyond the scope of this paper.

### 5.1 The Overall Effect of the IEB on University GPA

As a starting point, an OLS regression with university GPA as the dependent variable is reasonable in order to estimate an average effect of the IEB school-leaving examination. In this model specification, the more detailed school classification variable is used in order to ensure that the true effect of the IEB examination is not confounded by the effects of varied resource availability at schools. A number of different specifications of the model were run, but the preferred specification is presented in Table 9, below. Table 9 also presents the results of the faculty-specific OLS regressions, which use the same basic functional form as the pooled OLS model, but fit a model to each faculty individually in order to determine whether the IEB exam has differential effects depending on a student's faculty of study.

To begin, it is important to note that the pooled OLS regression is only run on approximately a quarter of the available population of students. This is due to sparse population of the socio-economic status data. For example, information of parents' and grandparents' education levels are only populated for approximately half of the observations in the data, which means that, without imputation, the available sample for the regression shrinks substantially. As a result, there exists a trade-off between sample size and including controls for socio-economic status. Given the importance of socio-economic status in the literature on South African educational attainment (for example, Bhorat & Oosthuizen, 2008; van Broekhuizen et al., 2016 van der Berg, 2008; van der Berg & Burger, 2003), it was deemed more important to control for these socio-economic status variables as the resulting sample size is still relatively large. Since these variables do not constitute the effect of interest, imputation could be used to bolster the sample size without biasing the coefficients of interest (Wooldridge, 2010), however, this is not done in this paper.

As far as the purpose of this paper goes, the results of interest to the research question are summarised in the first 14 lines of Table 9. With a base category of Former African non-IEB schools, it is immediately clear that IEB schools provide a statistically significant, and practically large, impact on university GPA. The size of the effect in the pooled regression ranges from a 1.6 percentage point effect to a 6.5 percentage point effect, *ceteris paribus*.[14]

[14] It is important to remember that these are effects on overall GPA, which is the average of all the courses a student takes in their first year of study.

Table 9: OLS regression results on university GPA, 2012 to 2017

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | | Faculty Regressions | | | | | |
| | Pooled OLS | COM | EBE | HUM | LAW | MED | SCI |
| **School board (Former African as base)** | | | | | | | |
| Model C IEB | 2.232*** | 2.812** | 3.216** | 1.439 | -14.735** | 3.804** | 1.905 |
| | (0.727) | (1.334) | (1.483) | (1.674) | (6.934) | (1.746) | (2.323) |
| Model C non-IEB | 0.691 | 1.033 | 2.048** | 0.485 | -13.316** | 0.620 | -1.594 |
| | (0.497) | (0.907) | (1.001) | (1.186) | (6.545) | (1.106) | (1.760) |
| Former Coloured/Indian (IEB) | 5.580*** | 6.492*** | 7.114*** | 5.298 | | | 6.428** |
| | (1.484) | (2.223) | (2.189) | (3.775) | | | (3.236) |
| Former Coloured/Indian | 1.698* | 2.441 | 2.035 | 1.872 | -6.960 | 0.584 | 2.363 |
| | (0.894) | (1.950) | (1.803) | (1.856) | (8.496) | (1.878) | (2.399) |
| Post-Apartheid school IEB | 6.485*** | 6.738*** | 8.582*** | 6.520*** | -9.704 | 5.028** | 2.092 |
| | (0.925) | (1.892) | (1.942) | (1.825) | (11.088) | (2.526) | (3.106) |
| Post-Apartheid school (non-IEB) | 1.047 | -0.945 | -2.866 | 2.205 | | -0.022 | 5.632 |
| | (1.397) | (2.261) | (4.143) | (2.840) | | (2.236) | (3.842) |
| Independent schools | 1.605** | 3.370*** | 2.899** | -0.055 | -21.521** | 2.772 | -0.165 |
| | (0.656) | (1.122) | (1.340) | (1.551) | (10.525) | (1.779) | (2.449) |
| Matric average | 0.852*** | 1.108*** | 0.828*** | 0.800*** | 0.928** | 0.575*** | 1.348*** |
| | (0.031) | (0.058) | (0.064) | (0.062) | (0.434) | (0.086) | (0.100) |
| Maths | 5.466*** | 0.157 | | 6.424*** | 13.803** | 5.601* | -1.413 |
| | (0.759) | (2.748) | | (0.853) | (5.550) | (3.286) | (4.553) |
| **Gender (Female as base)** | | | | | | | |
| Male | 0.009 | 1.127** | 0.375 | 0.332 | -0.555 | -1.265* | 1.675 |
| | (0.331) | (0.559) | (0.687) | (0.754) | (3.324) | (0.757) | (1.048) |
| **Race (African as base)** | | | | | | | |
| Asian/Indian | -1.647** | -2.187* | -3.603** | -0.214 | -13.390** | 5.319*** | -3.934 |
| | (0.719) | (1.161) | (1.461) | (1.514) | (6.523) | (1.709) | (2.465) |
| Coloured | -0.581 | -0.524 | 0.064 | -1.168 | -13.797** | 1.179 | -1.807 |
| | (0.687) | (1.197) | (1.528) | (1.332) | (5.209) | (1.626) | (2.451) |
| White | 1.771*** | 1.281 | 0.171 | 0.455 | -12.645 | 9.221*** | 1.474 |
| | (0.641) | (1.065) | (1.318) | (1.283) | (7.916) | (1.588) | (2.205) |
| International/Other | -0.884 | -0.789 | -1.918 | -2.272* | -16.141*** | 5.822*** | 1.242 |
| | (0.704) | (1.117) | (1.674) | (1.277) | (5.550) | (1.758) | (2.543) |
| **Faculty (Commerce as base)** | | | | | | | |
| Engineering & Built Environ. | -1.418*** | | | | | | |
| | (0.379) | | | | | | |
| Humanities | 2.464*** | | | | | | |
| | (0.423) | | | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Law | -2.148* | | | | | | |
| | (1.138) | | | | | | |
| Medicine | 3.123*** | | | | | | |
| | (0.442) | | | | | | |
| Science | -1.382*** | | | | | | |
| | (0.529) | | | | | | |
| First choice | 1.857*** | 1.146** | 2.892*** | 2.599*** | -0.572 | 1.247 | 0.150 |
| | (0.296) | (0.499) | (0.649) | (0.592) | (3.220) | (0.959) | (0.951) |
| Average NBT | 0.026 | 0.097*** | 0.041 | -0.068* | -0.162 | -0.145*** | 0.152** |
| | (0.019) | (0.032) | (0.042) | (0.036) | (0.216) | (0.053) | (0.066) |
| Maths NBT | -0.537 | 0.824 | | -1.407** | -4.328 | 7.077* | |
| | (0.650) | (1.799) | | (0.711) | (4.142) | (3.822) | |
| Financial aid | 1.405*** | 0.296 | -0.639 | 2.750*** | 7.837 | 0.312 | 1.696 |
| | (0.408) | (0.766) | (1.027) | (0.802) | (4.945) | (0.773) | (1.297) |
| **Residence status (Not in res as base)** | | | | | | | |
| Catered res | -0.561* | -0.988* | 0.273 | -0.931 | -2.665 | -0.487 | -1.489 |
| | (0.325) | (0.567) | (0.710) | (0.664) | (3.520) | (0.749) | (1.192) |
| Self-catered res | -1.151 | -3.310 | 2.481 | -2.213 | 1.456 | 0.356 | 0.251 |
| | (0.994) | (2.032) | (1.907) | (1.583) | (4.994) | (3.781) | (4.043) |
| Constant | -7.659 | -25.376*** | -16.535 | 18.481** | 32.387 | 12.204 | -61.081*** |
| | (5.829) | (6.931) | (11.065) | (8.361) | (50.346) | (12.899) | (16.065) |
| Observations | 6,365 | 1,851 | 1,087 | 1,887 | 118 | 742 | 680 |
| R-squared | 0.342 | 0.377 | 0.356 | 0.337 | 0.614 | 0.435 | 0.474 |

Source: UCT student records data (2018), Department of Basic Education (2018), and Human Science Research Council (2000).

Note: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses; Controls for parents' education level, grandparents' education level, school-level characteristics and infrastructure, home language, grant recipient status, year of first registration at UCT, and year of matriculation included, but not reported; Gender categories for transgender and unclassified are included, however, due to small sample size, point estimates of the effects have been omitted to avoid confusion

A further point, which is important to note in the pooled OLS regression, is that the comparison of non-IEB schools to the base category generally show statistically insignificant differences. This indicates that the students from various different non-IEB schools, despite their schools' Apartheid classifications, and hence differing resource availability beyond that which was controlled for, do not seem to have vastly different university-readiness. Perhaps this indicates that the large effects of the IEB exam are independent of resource availability, and as such, there is validity to the claim that the IEB better prepares students for university education (IEB, 2015).

In order to further investigate this hypothesis, a second specification of the pooled OLS regression was run where resource availability measures at schools, such as the presence of computers for learning, the presence of science laboratories at a school, and the number of desks per student, were interacted with school classification. These variables, for the most part, were individually insignificant, with the exception of the interaction between the post-Apartheid IEB schools and the presence of a science lab, which appeared negative and significant. This suggests that for post-Apartheid IEB schools, the presence of a science lab decreases academic performance relative to post-Apartheid IEB schools without a science lab, however, the sample size for this point estimate is small, and as a result, this estimate is likely highly spurious. Taking this into account, when a test for joint significance of the interaction terms (not including the science lab interaction for post-Apartheid schools) was conducted, the F-statistic was 1.08, with a corresponding p-value of 0.3765, indicating that the resource-school board interaction terms are jointly insignificant, providing further support to the hypothesis that the IEB effect is independent of resource availability.

The effect of the IEB exam can also be seen across the various faculties at UCT in columns (2) to (7).[15] The IEB effect is between 2.9 and 8.6 percentage points for students studying in the Commerce, Engineering and Medicine faculties, all else constant. Interestingly, the effect of the IEB exam on university GPA is statistically insignificant for the Science faculty. This is strange given the large positive effects present for similar subjects in Medicine and Engineering. Students in the Humanities faculty also see no positive impact on their GPA from writing the IEB exam, *ceteris paribus*.

[15] It should be noted that due to the small sample size in the regression for the Law faculty (column (5)), these results may be spurious and should be interpreted with extreme caution.

Further interesting results which appear from Table 9 include the strong and positive impact of one's matric results on university performance. This supports the theory that educational attainment is cumulative (Hanushek, 1997). It also seems that once matric marks are controlled for, the NBT scores lose their explanatory power over university GPA. This result is interesting in that it suggests that perhaps the current secondary school education level is a strong signal of a student's ability, and does well in predicting their university success.

A number of studies have also considered the effect of psychological factors and motivation towards studying on university performance (Fraser & Killen, 2005; Parker et al., 2006). To this end, a dummy variable indicating whether a student was registered for their first choice of degree or not was included in the model. This variable has appeared as statistically significant and as having an effect of 1.9 percentage points on a student's GPA should they be registered for their first choice of degree rather than their second choice, all else equal. This is a rather strong result, which supports the argument made by Fraser & Killen (2005) that some of the most important psychological drivers of university performance come from interest in the subject matter and motivation. Although being registered for one's first choice of degree is not an infallible proxy, it is a serviceable one, and the results it provides are potentially the doorway to further research on motivation and psychological factors influencing university performance, which lie beyond the scope of this paper.

As was mentioned in section 4.3.3, the effect of certain covariates may not be constant across the entirety of a distribution. Thus, in the vein of Bhorat and Oosthuizen (2008), quantile regressions were run in order to compare the results of covariates at the $10^{th}$, $25^{th}$, $50^{th}$, $75^{th}$ and $90^{th}$ percentiles of the distribution. These results are presented in Table 10, below.

A first key result is that the IEB examinations have the largest effect at the bottom of the distribution – the impact at the $10^{th}$ percentile of the distribution ranges from 3.3 percentage points to 10.1 percentage points, all else equal. Hereafter, the *ceteris paribus* effect that the IEB exam has on university GPA diminishes the further up the distribution one moves. This seems reasonable, however: If one assumes that those students with higher ability will perform to a higher level at university, then whether these students wrote an IEB or DBE exam becomes less and less relevant. In essence, the students at the top end of the distribution will still perform to an exceptional level, whether they wrote an IEB exam or not. This being said, the effect of the IEB exam is still positive and significant, and in fact, it seems to increase from the $75^{th}$ percentile to the $90^{th}$ percentile.

However, a hypothesis test across models (4) and (5) in Table 10 indicates that this increase is not statistically significant, and in fact the effects at the $75^{th}$ and the $90^{th}$ percentile could be equal. This finding is consistent with that of Smith and Naylor (2001), who also find that the effect of A-level results on university performance is highest for those with lower A-level point scores.

Table 10: Quantile regression results on university GPA, 2012 to 2017

| | (1)<br>q10 | (2)<br>q25 | (3)<br>q50 | (4)<br>q75 | (5)<br>q90 |
|---|---|---|---|---|---|
| **School board (Former African as base)** | | | | | |
| Model C IEB | 3.527** | 2.444** | 1.852** | 0.853 | 1.984** |
| | (1.711) | (1.206) | (0.861) | (0.585) | (0.775) |
| Model C non-IEB | 3.156*** | 0.536 | 0.028 | -0.225 | 0.167 |
| | (1.171) | (0.597) | (0.589) | (0.421) | (0.559) |
| Former Coloured/Indian (IEB) | 7.040* | 6.362*** | 3.825** | 1.540 | 2.361 |
| | (4.110) | (1.864) | (1.744) | (1.256) | (3.460) |
| Former Coloured/Indian | 2.171 | 1.742* | 0.946 | 1.570** | 1.234 |
| | (1.903) | (0.957) | (0.816) | (0.743) | (1.360) |
| Post-Apartheid school IEB | 10.148*** | 7.087*** | 5.557*** | 3.685*** | 4.172*** |
| | (2.165) | (1.529) | (1.423) | (0.804) | (1.181) |
| Post-Apartheid school (non-IEB) | 1.734 | -1.336 | 0.107 | 0.438 | 3.628 |
| | (2.149) | (2.090) | (1.638) | (0.995) | (3.245) |
| Independent schools | 3.333* | 1.580 | 1.727** | 1.406** | 1.559** |
| | (1.810) | (1.160) | (0.839) | (0.596) | (0.779) |
| | | | | | |
| Matric average | 1.063*** | 0.988*** | 0.791*** | 0.707*** | 0.637*** |
| | (0.043) | (0.032) | (0.030) | (0.029) | (0.035) |
| Maths | 11.705*** | 6.083*** | 3.471*** | 3.289*** | 2.072** |
| | (2.759) | (1.293) | (0.835) | (0.664) | (0.880) |
| **Gender (Female as base)** | | | | | |
| Male | -0.402 | 0.026 | 0.167 | -0.125 | 0.930** |
| | (0.657) | (0.425) | (0.304) | (0.298) | (0.445) |
| | | | | | |
| **Race (African as base)** | -2.131 | -1.711 | -0.909* | -1.163 | -2.669*** |
| Asian/Indian | (1.628) | (1.165) | (0.540) | (0.802) | (0.972) |
| | 0.159 | -0.302 | -0.346 | 0.024 | -0.546 |
| Coloured | (1.449) | (0.950) | (0.676) | (0.662) | (0.902) |
| | 4.033*** | 2.073** | 1.825*** | 1.128* | -0.278 |
| White | (1.396) | (0.901) | (0.644) | (0.679) | (0.840) |
| | -1.487 | -0.370 | -0.157 | 0.206 | 0.471 |
| International/Other | (1.847) | (0.915) | (0.623) | (0.809) | (0.663) |
| | | | | | |
| **Faculty (Commerce as base)** | | | | | |
| Engineering & Built Environ. | -1.418* | -1.461*** | -1.786*** | -2.075*** | -2.147*** |
| | (0.825) | (0.406) | (0.379) | (0.318) | (0.598) |
| Humanities | 2.821*** | 3.311*** | 3.163*** | 1.522*** | 0.102 |

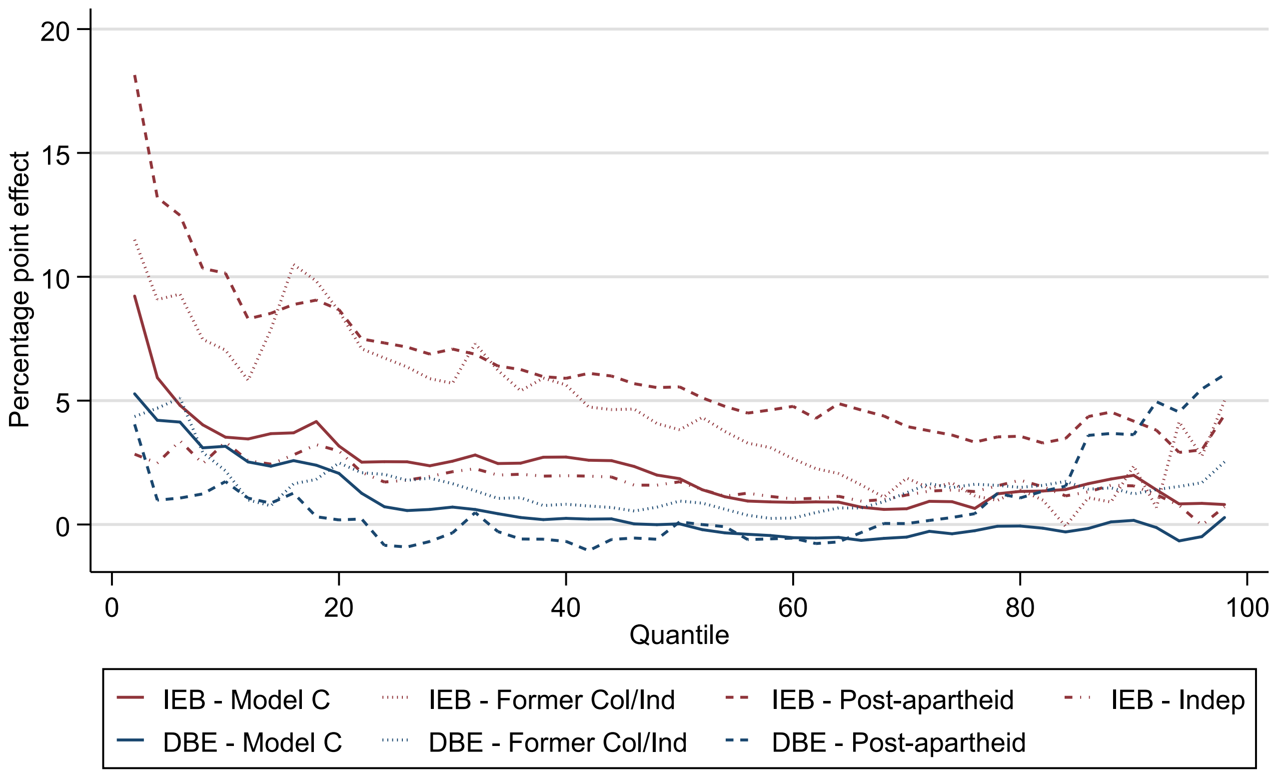
| | | | | | |
|---|---|---|---|---|---|
| | (0.802) | (0.461) | (0.385) | (0.358) | (0.501) |
| Law | 0.443 | 1.534 | -0.955 | -3.316*** | -4.762*** |
| | (6.171) | (1.936) | (0.631) | (0.639) | (0.866) |
| Medicine | 2.373*** | 1.908*** | 3.139*** | 2.997*** | 2.747*** |
| | (0.764) | (0.671) | (0.568) | (0.519) | (0.506) |
| Science | -5.190*** | -1.536** | -0.639 | 0.089 | 1.098* |
| | (1.299) | (0.608) | (0.474) | (0.522) | (0.597) |
| First choice | 3.104*** | 2.213*** | 1.639*** | 1.159*** | 0.984*** |
| | (0.661) | (0.361) | (0.293) | (0.197) | (0.331) |
| Average NBT | -0.039 | 0.014 | 0.071*** | 0.102*** | 0.123*** |
| | (0.038) | (0.024) | (0.019) | (0.020) | (0.025) |
| Maths NBT | -0.678 | -1.525* | -0.330 | -1.076*** | -0.570 |
| | (1.820) | (0.821) | (0.592) | (0.372) | (0.590) |
| Financial aid | 1.048* | 0.893* | 1.081** | 0.847** | 0.725 |
| | (0.570) | (0.521) | (0.431) | (0.429) | (0.538) |
| **Residence status (Not in res as base)** | | | | | |
| Catered res | -0.903* | -0.839** | -0.495 | -0.352 | -0.199 |
| | (0.511) | (0.398) | (0.301) | (0.332) | (0.436) |
| Self-catered res | -2.186 | -1.760 | -0.679 | 0.616 | -0.206 |
| | (2.971) | (1.266) | (0.780) | (0.777) | (0.642) |
| Observations | 6,365 | 6,365 | 6,365 | 6,365 | 6,365 |

Source: UCT student records data (2018), Department of Basic Education (2018), and Human Science Research Council (2000).

Note: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses; Controls for parents' education level, grandparents' education level, school-level characteristics and infrastructure, home language, grant recipient status, year of first registration at UCT, and year of matriculation included, but not reported; Gender categories for transgender and unclassified are included, however, due to small sample size, point estimates of the effects have been omitted to avoid confusion.

This finding is further supported by Figure 7, below. This figure plots out the effect of the various schooling boards on university GPA across the entirety of the distribution. All effects are plotted relative to the base category of Former African DBE schools. What is clear to see is that the effects of IEB schools, as shown by the red lines, are generally higher than the effects of corresponding DBE schools, which are depicted in blue. Furthermore, the effect of the IEB examination is strongest at the lowest end of the distribution, with effects of up to approximately 18 percentage points for post-Apartheid IEB schools. However, these effects decline as one reaches the top-performing students, where the effect of writing an IEB school-leaving exam is not substantially different from the effect of having written the DBE examinations. This is consistent with what was found in the quantile regression analysis presented in Table 10, above. An advantage of the graphical representation is that it depicts the effects across the entire distribution, rather than just at selected points, making it a valuable tool to determine how the IEB examination board may impact on students across the entire distribution of grades.

Figure 7: Graph of the IEB effect on university GPA across the entire distribution of students




Source: Own calculations from UCT student records data (2018), Department of Basic Education (2018) & Human Science Research Council (2000).
Note: All effects are relative to base category of Former Black DBE schools

Once again, the effect of a student's matric mark is positive and significant across the entire distribution. However, the effect does shrink from a 1.1 percentage point effect to a 0.6 percentage point effect as one moves up the distribution. Furthermore, having taken maths as a subject in high school has a substantial effect of 11.7 percentage points on an individual's GPA at the bottom of the distribution, which shrinks to only a 2.1 percentage point effect at the 90$^{th}$ percentile. The combination of these two factors indicate that all else constant, students who fall lower on the academic distribution are the ones who will benefit most from a stronger secondary education, a finding which is consistent with that of Smith and Naylor (2001). Furthermore, Hanzari et al. (2007) find that taking mathematics at school level is one of the most significant predictors of university success in the US, with strongly significant and practically large effects – a finding which has been replicated here, although more so at the bottom of the academic distribution.

According to faculty-related performance, it seems that all else constant, students in the Commerce faculty are strong performers, with only Humanities students and Medical students outperforming them across the majority of the distribution. The fact that there are large spreads of marks across the different faculties is consistent with the findings of McNabb et al. (2002), who argue that even after controlling for a number of demographic and socio-economic characteristics, there can be strong variation across faculties.

Finally, more in keeping with the methods adopted in international studies of university performance, the results of the binary choice probit on whether students passed or failed, and the ordered probit on pass classification are presented below, in Table 11. The reported results are the average marginal effects in each case, which can be directly interpreted as an effect on the probability of observing the outcome of interest occurring (Wooldridge, 2010).

Table 11: Probit and ordered probit regression results on first-year performance, 2012 to 2017

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | | | **Ordered Probit ME** | | |
| VARIABLES | Probit ME | First class | Upper second | Lower second | Third class | Fail |
| **School board (Former African as base)** | | | | | | |
| Model C IEB | 0.051** | 0.038*** | 0.019*** | 0.007*** | -0.026*** | -0.037*** |
| | (0.023) | (0.014) | (0.007) | (0.002) | (0.010) | (0.013) |
| Model C non-IEB | 0.036** | 0.006 | 0.003 | 0.002 | -0.004 | -0.007 |
| | (0.015) | (0.008) | (0.004) | (0.003) | (0.006) | (0.009) |
| Former Coloured/Indian (IEB) | - | 0.101* | 0.043*** | -0.001 | -0.065** | -0.077*** |
| | | (0.051) | (0.016) | (0.012) | (0.029) | (0.026) |
| Former Coloured/Indian | 0.042* | 0.021 | 0.011 | 0.005* | -0.015 | -0.022 |
| | (0.022) | (0.014) | (0.007) | (0.003) | (0.010) | (0.014) |
| Post-Apartheid school IEB | 0.107*** | 0.120*** | 0.048*** | -0.006 | -0.076*** | -0.086*** |
| | (0.024) | (0.026) | (0.008) | (0.008) | (0.015) | (0.014) |
| Post-Apartheid school (non-IEB) | -0.008 | 0.001 | 0.000 | 0.000 | -0.000 | -0.001 |
| | (0.044) | (0.021) | (0.012) | (0.007) | (0.015) | (0.025) |
| Independent schools | 0.045** | 0.040*** | 0.020*** | 0.007*** | -0.028*** | -0.039*** |
| | (0.020) | (0.011) | (0.006) | (0.002) | (0.008) | (0.011) |
| Matric average | 0.012*** | 0.015*** | 0.008*** | 0.003*** | -0.010*** | -0.015*** |
| | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) | (0.001) |
| Maths | 0.116*** | 0.075*** | 0.039*** | 0.015*** | -0.052*** | -0.076*** |
| | (0.019) | (0.012) | (0.006) | (0.003) | (0.008) | (0.012) |
| **Gender (Female as base)** | | | | | | |
| Male | -0.005 | 0.004 | 0.002 | 0.001 | -0.003 | -0.004 |
| | (0.010) | (0.006) | (0.003) | (0.001) | (0.004) | (0.006) |
| **Race (African as base)** | | | | | | |
| Asian/Indian | -0.024 | -0.015 | -0.010 | -0.007 | 0.012 | 0.020 |
| | (0.022) | (0.011) | (0.007) | (0.005) | (0.008) | (0.015) |
| Coloured | 0.006 | 0.002 | 0.001 | 0.001 | -0.002 | -0.002 |
| | (0.020) | (0.011) | (0.007) | (0.004) | (0.008) | (0.013) |
| White | 0.048*** | 0.046*** | 0.025*** | 0.009** | -0.034*** | -0.045*** |
| | (0.018) | (0.011) | (0.006) | (0.003) | (0.008) | (0.012) |
| International/Other | -0.020 | 0.011 | 0.007 | 0.004 | -0.008 | -0.013 |
| | (0.020) | (0.011) | (0.006) | (0.004) | (0.008) | (0.013) |
| **Faculty (Commerce as base)** | | | | | | |
| Engineering & Built Environ. | -0.015 | -0.033*** | -0.021*** | -0.014*** | 0.024*** | 0.045*** |
| | (0.014) | (0.006) | (0.004) | (0.003) | (0.004) | (0.008) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Humanities | 0.037*** | 0.049*** | 0.023*** | 0.003*** | -0.032*** | -0.043*** |
| | (0.012) | (0.008) | (0.004) | (0.001) | (0.005) | (0.007) |
| Law | 0.032 | -0.029** | -0.018* | -0.012 | 0.021** | 0.038* |
| | (0.027) | (0.014) | (0.010) | (0.008) | (0.010) | (0.021) |
| Medicine | 0.081*** | 0.080*** | 0.034*** | -0.001 | -0.050*** | -0.063*** |
| | (0.013) | (0.010) | (0.004) | (0.002) | (0.006) | (0.007) |
| Science | -0.080*** | -0.014* | -0.008* | -0.004* | 0.010* | 0.017* |
| | (0.017) | (0.007) | (0.004) | (0.003) | (0.005) | (0.009) |
| First choice | 0.048*** | 0.028*** | 0.015*** | 0.005*** | -0.019*** | -0.029*** |
| | (0.008) | (0.005) | (0.003) | (0.001) | (0.003) | (0.005) |
| Average NBT | -0.000 | 0.001*** | 0.001*** | 0.000*** | -0.001*** | -0.001*** |
| | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Maths NBT | -0.022 | -0.014 | -0.007 | -0.003 | 0.010 | 0.015 |
| | (0.019) | (0.011) | (0.006) | (0.002) | (0.007) | (0.011) |
| Financial aid | 0.015 | 0.019*** | 0.010*** | 0.004*** | -0.013*** | -0.019*** |
| | (0.011) | (0.007) | (0.004) | (0.001) | (0.005) | (0.007) |
| **Residence status (Not in res as base)** | | | | | | |
| Catered res | -0.003 | -0.011* | -0.006* | -0.002* | 0.008* | 0.012* |
| | (0.010) | (0.006) | (0.003) | (0.001) | (0.004) | (0.006) |
| Self-catered res | -0.027 | 0.006 | 0.003 | 0.001 | -0.004 | -0.006 |
| | (0.022) | (0.014) | (0.007) | (0.002) | (0.010) | (0.013) |
| Observations | 6,374 | 6,423 | 6,423 | 6,423 | 6,423 | 6,423 |

Source: UCT student records data (2018), Department of Basic Education (2018), and Human Science Research Council (2000).

Note: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses; Controls for parents' education level, grandparents' education level, school-level characteristics and infrastructure, home language, grant recipient status, year of first registration at UCT, and year of matriculation included, but not reported; Gender categories for transgender and unclassified are included, however, due to small sample size, point estimates of the effects have been omitted to avoid confusion.

To begin, by examining column (1), the marginal effects of the binary choice probit model reflect a similar trend to before: Those students who wrote IEB examinations seem to have an increased probability of passing their degrees than do those students who did not write IEB exams. Once again, post-Apartheid schools offering IEB exams have the largest impact, with the probability of passing your first year at university being almost 11 percentage points higher than if you had attended a Former African school. However, attending other IEB-offering schools also provide an approximate 5 percentage point increase in the probability of passing first year over those students who attended Former African schools, *ceteris paribus*. In this case, however, the impact of attending non-IEB schools is non-trivial, and attending an Model C school or Former Indian/Coloured school, even when they are not an IEB school, increases an individual's chance of passing their first year by approximately 3.6 and 4.2 percentage points, respectively. The impact of attending an IEB-offering school is higher than a non-IEB school in each category, indicating that there is still a positive impact of the IEB examination on final pass rates, *ceteris paribus*.

When considering the ordered probit, in columns (2) to (6), one can see that the likelihood of obtaining a 1$^{st}$ class, upper 2$^{nd}$ or lower 2$^{nd}$ class pass is higher for students who wrote IEB school-leaving exams, while the likelihood of obtaining a 3$^{rd}$ class pass or failing is lower for those who wrote IEB school-leaving exams, all else equal. In this specification of the model, in fact, the impacts of non-IEB examinations across the various school classifications are once again insignificant, indicating that there is no real difference in the distribution of performance across different classifications of DBE schools. This finding is in contradiction to the findings from studies done in the UK, where it has been found that attending an independent school leads to a decrease in the probability of obtaining a good degree, *ceteris paribus* (McNabb et al., 2002; Ogg et al., 2009; Smith & Naylor, 2001; Smith & Naylor, 2005). However, as has been mentioned previously, there are fundamental differences in the set-up of the education systems in the UK and South Africa. Where in the UK all students write a common set of A-level exams, in South Africa, the two types of schools are examined by different examining bodies, with different final exams. This means that in the UK, although independent schools may benefit from smaller classes and more qualified teachers, the students are not necessarily being taught differently to their peers in LEA schools[16] (Smith & Naylor, 2001).

[16] LEA (or Local Education Authority) schools are the UK equivalent of South African DBE schools.

This section has provided a brief overview and discussion of the results of the econometric investigation into the impact of the IEB matric examination on tertiary academic outcomes. In general, the findings seem to fall positively for the IEB, in that there seems to be a positive impact on university GPA, pass rates and the probability of passing one's first year of study with a 2nd class pass or higher. However, although there seems to be a positive effect of the IEB on the whole, it is unclear as to whether this effect is as the result of teaching effects or due purely to the different method in which the IEB chooses to assess their students. The following subsection presents the results from the decomposition exercises undertaken in order to isolate the effect of purely the testing method employed by the IEB.

### 5.2 The Decomposition of the IEB Effect

This subsection of the paper presents the results for the isolation of a pure testing effect of the IEB on university GPA, the method for which was laid out in Section 4.3.6. The results of the two models discussed in that section are presented below, in

Table 13.

Due to collinearity of school indicator variables with the more detailed school board classification, the basic IEB dummy had to be used in the specification of model (1). This model includes school fixed effects, which means that the IEB coefficient estimate relies on changes of examination board within schools over the period of interest. In order to make sure that this coefficient is not spuriously estimated, we consider Table 12, below.

It is clear from the table that in the full sample, there are 20 schools which underwent a change of examination board between 2012 and 2017, however, only 3 of these schools are included in the final regression due to data limitations.[17] This is not ideal, however, it is clear that 497 observations of the total 6690 observations (approximately 7.5 percent of the sample) are students who matriculated from a school that changed examination bodies. Although not a large proportion, this is likely to still provide a reasonable estimate of the effect of changing from a DBE exam to an IEB exam.

[17] These schools are St Cyprian's Girls' School, Harvest Christian School, and Crawford College Sandton.

Table 12: Breakdown of within-school variation of examination board

| | Full Sample | | Sample for Analysis | |
|---|---|---|---|---|
| | **Students** | **Schools** | **Students** | **Schools** |
| **DBE Only** | 15 892 | 1 616 | 4 643 | 246 |
| **IEB Only** | 4 758 | 148 | 1 550 | 35 |
| **Switching Schools** | 5 123 | 20 | 497 | 3 |
| | 25 773 | 1 784 | 6 690 | 284 |

Source: UCT student records data (2018), Department of Basic Education (2018), and Human Science Research Council (2000).

Noting the data limitations present in estimating model (1), if one considers the results of the school fixed effects regression, one can see that the premium from the IEB exam is large and statistically significant at almost 6 percentage points. This is particularly large, falling at the top end of the range of estimated effects in the previous pooled OLS model, indicating, perhaps, that the majority of the estimated effect above is as a result of the difference in testing methods rather than from differences in teaching quality.

Interestingly, in this case, the effect of a one percentage point increase in a learner's matric grade average now has an effect on their university GPA closer to parity than before, all else equal. The premium available in the Medicine and Humanities faculties are still observed strongly in this model, as well as the GPA penalties from the Law, Science and Engineering faculties, relative to Commerce. Further, the effect of race on university GPA seems to be generally insignificant, however, this would likely be explained by the fact that South Africa's schools are still broadly divided by race, and by controlling for school-level effects, these racial disparities are taken into account.

Table 13: Regression results for decomposition of IEB effect

| | (1) | (2) |
|---|---|---|
| | School FE | Net Teaching |
| IEB | 5.927*** | |
| | (1.749) | |
| **School board (Former African as base)** | | |
| Model C IEB | | 2.368*** |
| | | (0.726) |
| Model C non-IEB | | 0.768 |
| | | (0.497) |
| Former Coloured/Indian (IEB) | | 5.690*** |
| | | (1.475) |
| Former Coloured/Indian | | 1.681* |
| | | (0.895) |
| Post-Apartheid school IEB | | 6.611*** |
| | | (0.919) |
| Post-Apartheid school (non-IEB) | | 1.092 |
| | | (1.398) |
| Private schools | | 1.704*** |
| | | (0.654) |
| NBT (net of teaching) | | 0.026 |
| | | (0.019) |
| Matric average | 0.955*** | 0.874*** |
| | (0.026) | (0.025) |
| Maths | 4.812*** | 5.159*** |
| | (0.755) | (0.600) |
| **Faculty (Commerce as base)** | | |
| Engineering & Built Environ. | -1.191*** | -1.346*** |
| | (0.382) | (0.376) |
| Humanities | 2.360*** | 2.546*** |
| | (0.431) | (0.397) |
| Law | -3.185*** | -2.049* |
| | (1.168) | (1.137) |
| Medicine | 2.834*** | 3.159*** |
| | (0.451) | (0.438) |
| Science | -1.917*** | -1.348** |
| | (0.556) | (0.530) |
| **Gender (Female as base)** | | |
| Male | 0.310 | 0.144 |
| | (0.432) | (0.317) |
| **Race (African as base)** | | |

| | (1) | (2) |
|---|---|---|
| Asian/Indian | -1.069 | -1.575** |
| | (0.780) | (0.722) |
| Coloured | -1.106 | -0.568 |
| | (0.741) | (0.687) |
| White | 1.322* | 1.871*** |
| | (0.689) | (0.641) |
| International/Other | -0.710 | -0.788 |
| | (0.744) | (0.707) |
| | | |
| Constant | 75.630*** | -8.049 |
| | (25.611) | (5.888) |
| | | |
| Observations | 6,690 | 6,365 |
| R-squared | 0.436 | 0.342 |

Source: UCT student records data (2018), Department of Basic Education (2018), and Human Science Research Council (2000).

Note: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses; Controls for parents' education level, grandparents' education level, school-level characteristics and infrastructure, home language, grant recipient status, year of first registration at UCT, residence status, financial aid status, first choice of degree, and year of matriculation included, but not reported; Gender categories for transgender and unclassified are included, however, due to small sample size, point estimates of the effects have been omitted to avoid confusion.

The second model, presented in column (2) serves as both a second measure of the decomposition of the IEB effect as well as a robustness check for the first specification. The residuals method of decomposing the IEB effect shows similar results to the school fixed-effects results, however, now the decomposition can be done across the more detailed categorisation of school boards. Once again, the IEB premium exists, and is between 1.7 and 6.6 percentage points, *ceteris paribus*. This regression further confirms the result found in the original pooled OLS model, which indicates that DBE schools, in general, show no premium over a Former African school, and as such the IEB effect is prevalent regardless of resource availability – a finding that can also be gleaned from model (1). For the most part, the results presented by model (2) are extremely similar to those presented by model (1), indicating that estimating the testing effect of the IEB exam seems to be relatively robust to changes in functional form, and is relatively consistent no matter the preferred choice of model.

## 5.3 Robustness Checks and Areas for Further Research

Throughout this paper, the key research question has been to determine the effect of the IEB school-leaving examination on university-level outcome variables. While the reported regression results in Section 5.1 are in accordance with expectations, it is important to ensure that the estimations are robust to changes in the functional form of the model.

Many of the regressions run previously acted as robustness checks for one another in some way: By running an ordered probit model, the validity of the binary probit model was checked, and by running the probit model, the consistency of the conclusions obtained through OLS was checked. However, over and above these internal checks, two new specifications of the models were run in order to confirm the validity of the presented results. These two new specifications were run including all the OLS, quantile, probit and ordered probit regressions. This way, one ensures that the entirety of the estimated regression effects are robust rather than simply a subset of them.

The first reparameterization of the model involved redefining the way in which the IEB schools were classified. Given that in a number of cases, the effect of non-IEB schools was insignificantly different from the base category of a Former African school, the second model proposed included simply a dummy for the IEB schools, as well as dummies for each of the Former Apartheid school classifications: Former White, former Coloured and post-Apartheid schools, with Former African schools acting as the base category once again. The IEB effect obtained through running these regressions are presented in Table 16 in Appendix B.

In general, the results are strikingly similar: The IEB dummy is positive and significant in the regressions modelling university GPA and pass rates, and it indicates statistically significant increases in a student's probability of achieving a first year pass of a 2$^{nd}$ class or higher if they wrote the IEB exams. Furthermore, the effect of the IEB exam shows similar behaviour across the distribution in the quantile regression results, with the largest effect occurring at the bottom of the distribution, and decreasing as one moves up the percentiles.

A second robustness check was conducted by replacing the average NBT mark simply with the marks of the three NBT tests: mathematics, academic literacy and quantitative literacy. Given that there were a number of individuals who opted not to write the mathematics NBT, this could have introduced bias to the original specification of the model. Given the hypothesis that higher-performing students would opt to write the maths NBT, and that students on the top end of the ability distribution would perform well no matter their underlying education, this bias is expected to be negative. Thus, one would expect the coefficients on the IEB schools to be smaller than under the main specification.

Broadly, this is exactly what we see in the regression results presented in Table 17 in Appendix B. In general, the coefficients on the IEB school variables are smaller in magnitude than under the main specification, but they are still the same sign and generally the same level of significance. Thus, it can be concluded that the results presented here are relatively robust, and as such are a reasonable approximation of the effect of the IEB examination.

However, the results presented in this paper should not be taken as causal effects of the IEB exam on university performance in South Africa, as a whole. There are a number of shortfalls to this paper which could be addressed through further research.

The first of these problems is that of the specificity of the sample. In the studies conducted in the UK, Smith and Naylor (2001; 2005) and McNabb et al. (2002) had access to a central database of all university results across England, Scotland and Wales. This allowed them to investigate the effects of the different schooling systems across all universities in the country. Unfortunately, in this paper, data were only available for UCT, and as such the results presented here are not easily generalisable to the country as a whole. However, UCT is a university of international standard, and is widely regarded as the top university in Africa (THE, 2018). Thus, if the IEB exam is showing large and significant positive impacts at an internationally renowned university, one could argue that the IEB is preparing students to perform better at an international standard, and as such, should also be benefitting students at other universities. This argument, however, requires further investigation, which is left as potential further research.

Other difficulties experienced with this research paper included the lack of recent data available for some school-level variables. Although many variables that were needed could be generated from the given data, having a national school survey collecting information on infrastructure and resources at more frequent intervals would make the final results presented feel more tractable and less prone to bias due to having to use proxies.

The presence of schools that switch examination boards during the period under investigation is a powerful analytical tool. In order to exploit this in more detail, measures should be undertaken to limit loss of observations due to missing data. This would allow for the estimation of an effect of the IEB across multiple schools, and provide a more robust estimate of the IEB effect.

# 6. Concluding Remarks

This paper has investigated the impact of the IEB school-leaving examination on the first-year performance of UCT students through the use of sophisticated econometric techniques, and attempted to decompose the overall effect of the IEB examination into a teaching and a testing effect. Drawing on the insights of researchers who have conducted similar studies on universities in the UK (McNabb et al., 2002; Smith & Nayor, 2001; Smith & Naylor, 2005; Ogg et al., 2009), a framework for investigating the impact of schooling-level variables on university-level outcomes was developed.

Data challenges made it difficult to obtain variables to control for all the various characteristics which were suggested in the literature, however, by following inspiration from Bhorat and Oosthuizen (2008), a workable dataset was created. Through a combination of UCT administrative student records data, the Schools Register of Needs data and the SNAP Survey of Ordinary Schools, the dataset used in this paper was put together.

The results presented in this paper centred around three main dependent variables of interest: university GPA, which was calculated as a weighted average of a student's course marks; a binary variable indicating whether an individual had passed or failed their first year, with a cut-off mark of 50 percent; and a variable indicating the classification of the pass achieved at the end of the student's first year of study. The final specifications, which made use of the classification of pass are most commonly used in the literature, and as such, the inclusion of such a model allowed for this research to be compared to international papers by the likes of McNabb et al. (2002), Smith & Naylor (2001; 2005) and Ogg et al. (2009), who have all worked extensively on the determinants of university-level educational outcomes.

In South Africa, being in possession of an IEB matric certificate increases first year GPA by between 2.2 and 6.5 percentage points over a student from a Former African school, although this varies by faculty, with Medicine and Engineering seeing the largest positive effects, while the Humanities and Law faculties saw the smallest, and at times, negative effects. The impact of the IEB matric certificate is also greatest at the lower end of the performance distribution, with those at the 10$^{th}$ percentile seeing a GPA of between 3.3 and 10.1 percentage points higher than those students from Former African schools, while those at the 90$^{th}$ percentile were experiencing GPAs between 1.6 and 4.2 percentage points higher than students from Former African schools, *ceteris* *paribus*. The probability of a student passing their first year of studies was significantly improved by having written an IEB school-leaving exam, with students seeing increases of up to 10.7 percentage points over those students who attended Former African schools, *ceteris paribus*. Similarly, IEB students were found to have significantly higher probabilities – between 3.8 and 12 percentage points higher – of achieving at least a 2$^{nd}$ class pass at the end of their first year, compared to those students who attended Former African schools. Their probability of failure was also significantly lower than the probability of failure faced by students from Former African schools, all else equal. These results were all found to be robust to changes in the functional form.

The isolation of the pure testing effect of the IEB examinations was also found to be significant, and would benefit students by increasing university GPA by between 1.7 and 6.6 percentage points, no matter the estimation method used to conduct this decomposition. When comparing this to the effects observed in the pooled OLS model, it becomes clear that the testing effect of IEB exams is the dominant one in determining university success. This could indicate either that the exposure to the IEB's assessments is beneficial to the student, irrespective of the teacher they have, or else that teachers are truly aiming to teach for understanding, rather than simply to get students to pass their final exams. It is unclear at this juncture which, if any, of these effects this is.

Thus, this paper has presented a detailed investigation into the effects of the IEB school-leaving examination on university averages. Although it may not provide a direct causal effect of the IEB exam on national tertiary outcomes, it certainly supports the claims made by the IEB that their students are better prepared for tertiary education. Students who have been exposed to the IEB and have been taught to think more critically seem to be at a distinct advantage during their university years. However, as was discovered in the investigation presented in Appendix A, these self-same students potentially achieve lower final marks in their school-leaving exams, making it harder for them to actually enter the very universities for which they are prepared.

Although it is unclear exactly what aspect of IEB-administering schools it is which aids academic performance, it is clear that there is a premium attached to writing this exam. As a result, it is possible that some schools may be able to better prepare their students for tertiary education by adopting certain practices prevalent in IEB schools. The extent to which these practices are independent of socio-economic status is not clear, though, and so these results should be interpreted with caution.

It seems then that perhaps a reinvestigation of the South African education system is needed to ensure success and prosperity into the future. If it is possible to educate all students to think critically and engage with material at a deeper level, it will be possible to increase graduation rates from tertiary institutions, and as a result, start proactively fighting the poverty and inequality trap South African citizens find themselves in.

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# Appendix A: The School-level Effects of the IEB matric

This appendix to the main paper deals briefly with the results of an investigation into the effect of the IEB school-leaving examination on a student's final matric marks. As observed in Section 4.2 although the distribution of matric marks indicated that IEB and DBE students achieved similarly in their final school-leaving exams, the distribution of NBT results seemed to suggest that DBE final matric marks overstated a student's academic ability. Given that universities around South Africa do not treat students differently depending on their school examining board (IEB, 2015), it would be of interest to know whether there is a difference in school-leaving marks for DBE and IEB students, since these marks are used to determine university entrance, and as such could advantage or disadvantage one particular group of students over another.

To investigate this, a basic OLS regression based on the education production function theory of human capital was run in order to model the effect of the IEB exam on a student's final matric average, after innate ability is controlled for through the use of average NBT mark as a proxy. Two different specifications for the IEB exam were used: One which was simply a dummy for all IEB schools, and the second, which included the more detailed school classifications as outlined earlier in this paper. The results are presented in Table 14, below.

Table 14: OLS regression results for matric average, 2012 to 2017

| VARIABLES | (1)<br>Department*IEB | (2)<br>IEB dummy |
|---|---|---|
| Model C IEB | -4.078*** | |
| | (0.354) | |
| Model C non-IEB | -1.584*** | |
| | (0.242) | |
| Former Coloured/Indian (IEB) | -2.767*** | |
| | (0.897) | |
| Former Coloured/Indian | -1.290*** | |
| | (0.400) | |
| Post-Apartheid school IEB | -5.032*** | |
| | (0.507) | |
| Post-Apartheid school (non-IEB) | -2.414*** | |
| | (0.687) | |
| Independent schools | -3.183*** | |
| | (0.304) | |
| IEB | | -2.774*** |
| | | (0.210) |
| **Former Department (Former African as base)** | | |
| Former White | | -1.307*** |
| | | (0.178) |
| Former Coloured | | -0.955*** |
| | | (0.356) |
| Post-Apartheid school | | -2.088*** |
| | | (0.417) |
| Maths | 2.061*** | 2.079*** |
| | (0.221) | (0.220) |
| NBT Mean | 0.398*** | 0.398*** |
| | (0.007) | (0.007) |
| **Gender (Female as base)** | | |
| Male | -3.244*** | -3.257*** |
| | (0.148) | (0.147) |
| **Race (African as base)** | | |
| Asian/Indian | 1.115*** | 1.142*** |
| | (0.347) | (0.347) |
| Coloured | -0.688** | -0.737** |
| | (0.335) | (0.333) |
| White | 1.240*** | 1.215*** |
| | (0.307) | (0.306) |
| International/Other | -0.393 | -0.417 |
| | (0.325) | (0.324) |
| Constant | 44.916*** | 44.710*** |
| | (3.309) | (3.308) |
| Observations | 6,472 | 6,472 |
| R-squared | 0.517 | 0.516 |

Source: UCT student records data (2018), Department of Basic Education (2018), and Human Science Research Council (2000).

Note: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses; Controls for parents' education level, grandparents' education level, school-level characteristics and infrastructure, year matric was written, home language and grant recipient status included, but not reported; Gender categories for transgender and unclassified are included, however, due to small sample size, point estimates of the effects have been omitted to avoid confusion

An interesting point to note is that students who attend schools that are non-IEB, but were not classified as African under Apartheid seem to have achieved lower marks in their final exams. Given that it seems as if students in DBE schools have inflated final matric marks, it then seems as if the worst inflation of marks occurs in Former African schools, since other DBE students can expect to achieve between 1.5 and 2.4 percentage points lower at the end of matric, all else equal.

In both specifications of the model, it is clear that those students who write an IEB school-leaving exam attain significantly lower marks than their DBE counterparts, since the magnitude of the effect for each IEB school is larger than the correspondingly classified DBE school. In fact, when considering column (1) above, compared to their contemporary in a Former African non-IEB school, a student writing an IEB matric exam can expect to obtain an average matric mark between 2.7 and 5.0 percentage points lower, all else equal.

Given that universities do not differentiate students according to their examining board (IEB, 2015), this IEB penalty on one's matric average means that it is harder for students who write an IEB examination to gain access to university. Although the IEB (2015) claims that those students who write IEB and deserve to attend university do invariably get in, it is clear that students writing IEB exams have to perform at a higher level in order to compete with their DBE counterparts.

All this being said, this regression analysis suffers from bias due to it only accounting for students who attend UCT. In fact, the result may actually be saying exactly the opposite to what it seems: that IEB students have an easier time getting into university at UCT as they require lower marks to be awarded a place to study at this institution. However, the official standpoint of UCT is that students from DBE and IEB schools are not treated differentially when being offered a place to study. This implies that one has to conclude that students who write the IEB school-leaving exam are placed at a disadvantage when applying to university as for a given ability level, their final marks are lower. Thus, even though further research should be done to determine the true causal effect of writing an IEB matric on a student's average for the country as a whole, it certainly seems as if IEB students may be facing a disadvantage when it comes to gaining admission to university study.

## Appendix B: Additional Statistical Results and Tables

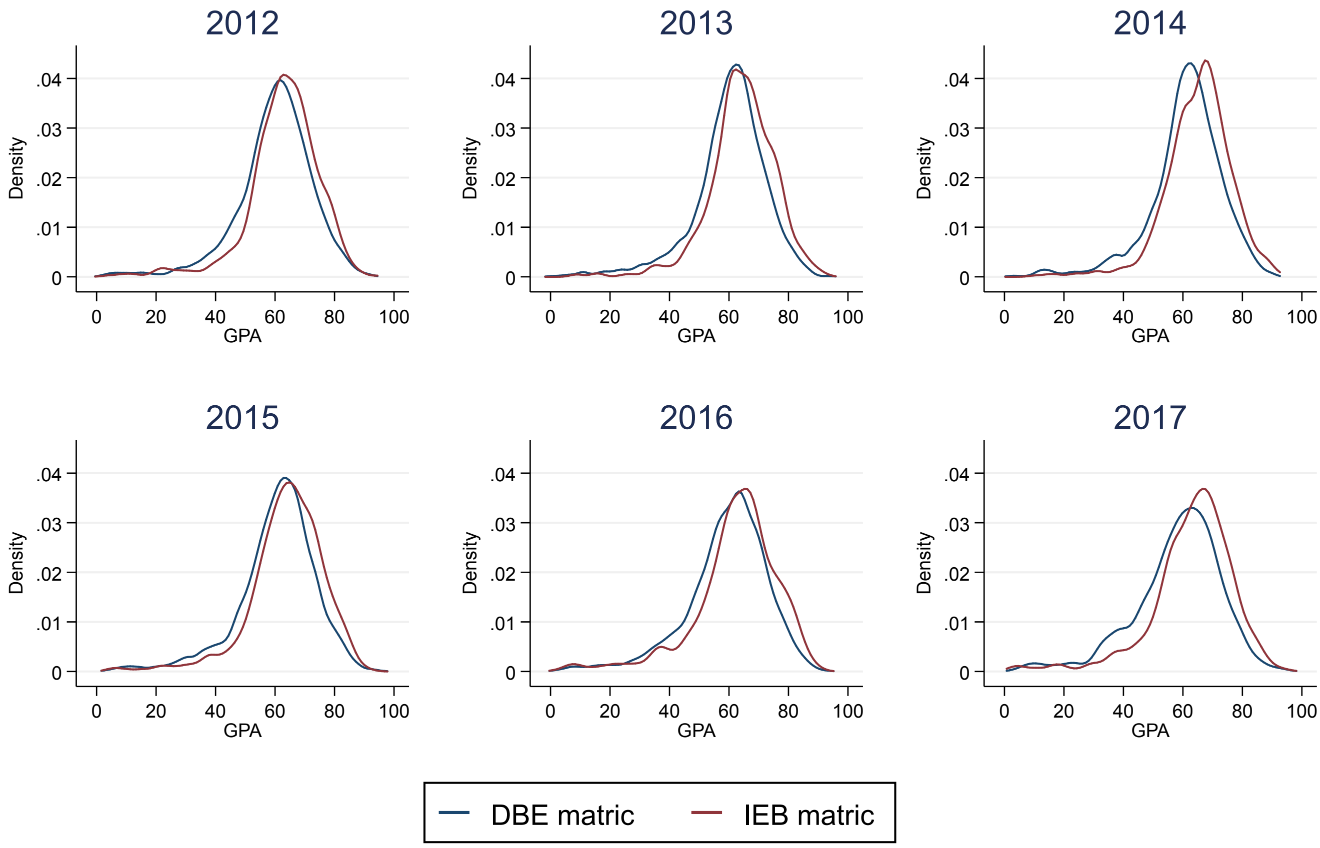
Table 15: Average university GPA for DBE and IEB schools by year, 2012 to 2017

| | **2012** | | | **2013** | | | **2014** | | | **2015** | | | **2016** | | | **2017** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **DBE** | **IEB** | | **DBE** | **IEB** | | **DBE** | **IEB** | | **DBE** | **IEB** | | **DBE** | **IEB** | | **DBE** | **IEB** | |
| **Gender** | | | | | | | | | | | | | | | | | | |
| Female | 60.50 | 63.09 | *** | 60.39 | 64.18 | *** | 61.24 | 64.78 | *** | 61.14 | 63.77 | *** | 59.63 | 61.67 | *** | 58.85 | 63.24 | *** |
| Male | 59.42 | 62.77 | *** | 60.05 | 64.53 | *** | 60.89 | 65.88 | *** | 59.88 | 64.21 | *** | 58.91 | 63.06 | *** | 57.71 | 62.79 | *** |
| **Faculty** | | | | | | | | | | | | | | | | | | |
| Commerce | 60.33 | 62.92 | *** | 61.17 | 65.23 | *** | 62.74 | 67.31 | *** | 60.70 | 64.35 | *** | 62.35 | 65.55 | *** | 61.32 | 65.91 | *** |
| Engineering & Built Environ. | 62.16 | 66.23 | *** | 61.79 | 64.70 | ** | 62.04 | 64.74 | ** | 60.89 | 63.80 | ** | 59.77 | 61.65 | * | 58.33 | 62.42 | *** |
| Humanities | 57.19 | 60.18 | *** | 57.95 | 62.12 | *** | 58.46 | 61.71 | *** | 58.70 | 60.34 | | 54.56 | 57.11 | ** | 53.67 | 58.88 | *** |
| Law | 55.76 | 49.46 | | 57.98 | 61.99 | | 56.11 | 63.65 | ** | 59.33 | 52.58 | * | 58.68 | 51.40 | ** | 58.10 | 58.88 | |
| Medicine | 65.03 | 70.47 | *** | 62.18 | 68.06 | *** | 63.75 | 68.17 | *** | 64.27 | 69.67 | *** | 65.88 | 69.29 | *** | 64.25 | 70.84 | *** |
| Science | 58.54 | 62.64 | ** | 59.12 | 65.05 | *** | 60.31 | 67.06 | *** | 60.57 | 67.90 | *** | 57.58 | 62.69 | *** | 57.23 | 63.10 | ** |
| **Race** | | | | | | | | | | | | | | | | | | |
| African | 56.98 | 59.37 | ** | 57.66 | 57.55 | | 58.88 | 60.44 | | 56.71 | 58.92 | ** | 56.89 | 57.02 | | 56.19 | 58.28 | * |
| Indian/Asian | 60.01 | 62.92 | | 61.34 | 64.39 | ** | 61.50 | 61.93 | | 61.40 | 62.82 | | 61.94 | 60.28 | | 60.86 | 60.70 | |
| Coloured | 57.27 | 59.20 | | 57.41 | 63.40 | ** | 58.87 | 61.94 | | 58.90 | 61.84 | | 57.43 | 57.95 | | 57.00 | 61.59 | * |
| White | 64.33 | 64.29 | | 64.51 | 67.01 | *** | 65.96 | 67.53 | ** | 65.52 | 66.41 | | 64.19 | 65.83 | ** | 66.87 | 68.13 | |
| Int/Other | 61.65 | 62.53 | | 64.26 | 63.58 | | 62.23 | 66.80 | ** | 61.43 | 63.14 | | 58.26 | 60.11 | | 55.73 | 59.37 | *** |
| **Home Language** | | | | | | | | | | | | | | | | | | |
| English | 61.56 | 63.60 | *** | 61.63 | 65.62 | *** | 62.43 | 66.18 | *** | 62.19 | 64.98 | *** | 60.86 | 63.45 | *** | 60.55 | 64.70 | *** |

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Afrikaans | 60.82 | 64.78 | | 60.58 | 66.17 | | 62.77 | 69.76 | *** | 64.12 | 67.83 | | 58.90 | 60.63 | | 61.63 | 66.67 | |
| Eng & Afr | 59.92 | 59.30 | | 59.16 | 64.28 | | 57.09 | 67.34 | *** | 62.18 | 68.95 | ** | 57.47 | 61.35 | | 54.21 | 62.35 | * |
| IsiXhosa | 56.79 | 57.35 | | 56.21 | 53.32 | | 56.65 | 56.66 | | 54.90 | 56.98 | | 54.02 | 56.31 | | 52.52 | 55.87 | |
| IsiZulu | 56.92 | 55.52 | | 58.43 | 58.04 | | 60.82 | 59.85 | | 57.25 | 55.61 | | 56.93 | 56.84 | | 55.83 | 52.63 | |
| Other African | 56.53 | 63.94 | *** | 58.03 | 59.64 | | 60.69 | 61.13 | | 59.01 | 60.57 | | 59.24 | 55.26 | ** | 57.10 | 59.12 | |
| Other Non-African | 60.38 | 62.47 | | 59.82 | 62.84 | | 60.39 | 63.15 | | 58.90 | 60.47 | | 60.77 | 61.82 | | 58.78 | 57.24 | |
| | | | | | | | | | | | | | | | | | | |
| **Residence** | | | | | | | | | | | | | | | | | | |
| Not in Res | 59.09 | 60.71 | ** | 59.82 | 61.23 | | 60.53 | 63.22 | *** | 61.75 | 63.10 | | 59.85 | 61.20 | | 60.33 | 64.68 | *** |
| Catered | 62.17 | 64.46 | *** | 60.95 | 65.76 | *** | 61.98 | 67.35 | *** | 60.30 | 64.41 | *** | 59.35 | 62.82 | *** | 57.91 | 63.04 | *** |
| Self-Catered | 57.13 | 58.92 | | 53.32 | . | | 50.52 | . | | 55.51 | 59.30 | * | 54.68 | 56.27 | | 52.24 | 58.81 | *** |
| | | | | | | | | | | | | | | | | | | |
| **Former Classification** | | | | | | | | | | | | | | | | | | |
| Former White | 61.47 | 63.10 | | 61.33 | 64.62 | *** | 62.58 | 64.60 | ** | 61.86 | 63.94 | * | 60.74 | 61.69 | | 60.54 | 63.94 | ** |
| Former Coloured | 58.00 | 58.50 | | 57.47 | 71.76 | *** | 58.09 | 62.89 | | 58.16 | 70.25 | ** | 56.21 | 62.26 | | 56.15 | 67.26 | ** |
| Former African | 57.85 | 63.01 | *** | 59.49 | 63.07 | *** | 59.48 | 65.10 | *** | 57.99 | 63.49 | *** | 57.48 | 62.22 | *** | 56.53 | 61.38 | *** |
| New Schools | 59.29 | 63.86 | *** | 59.67 | 64.21 | ** | 57.45 | 65.53 | *** | 57.43 | 64.65 | *** | 57.47 | 61.77 | ** | 52.62 | 64.39 | *** |
| | | | | | | | | | | | | | | | | | | |
| Financial Aid | 57.04 | 62.07 | *** | 58.10 | 59.11 | | 57.87 | 61.19 | | 59.08 | 65.55 | *** | 58.44 | 63.98 | *** | 57.54 | 65.95 | |

Source: UCT student records data (2018), Department of Basic Education (2018), and Human Science Research Council (2000).
Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 8: University GPA of first-year students by year, 2012 to 2017




Source: Own calculations using UCT student records data

Table 16: Robustness check 1: IEB effects from various regression specifications, IEB dummy only

| **Specification** | **Result** | **N** |
|---|---|---|
| Pooled OLS | 2.015*** | 6365 |
| | (0.451) | |
| **Faculty Regressions** | | |
| COM | 2.963*** | 1,851 |
| | (0.805) | |
| EBE | 2.951*** | 1,087 |
| | (0.956) | |
| HUM | 1.001 | 1,887 |
| | (1.011) | |
| LAW | -8.197 | 118 |
| | (7.037) | |
| MED | 3.197*** | 742 |
| | (1.146) | |
| SCI | 0.876 | 680 |
| | (1.646) | |
| **Quantile regression** | | |
| q10 | 2.629** | 6360 |
| | (1.125) | |
| q25 | 2.923*** | 6360 |
| | (0.772) | |
| q50 | 2.221*** | 6360 |
| | (0.353) | |
| q75 | 1.422*** | 6360 |
| | (0.313) | |
| q90 | 1.533*** | 6360 |
| | (0.460) | |
| Probit ME | 0.043*** | 6399 |
| | (0.015) | |
| **Ordered Probit ME** | | |
| First class | 0.042*** | 6423 |
| | (0.008) | |
| Upper second | 0.022*** | 6423 |
| | (0.004) | |
| Lower second | 0.008*** | 6423 |
| | (0.002) | |
| Third class | -0.029*** | 6423 |
| | (0.006) | |
| Fail | -0.043*** | 6423 |
| | (0.008) | |

Source: UCT student records data (2018), Department of Basic Education (2018), and Human Science Research Council (2000).

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$; Robust standard errors in parentheses; Controls for parents' education level, grandparents' education level, matric average, average NBT score, whether a student took pure mathematics at school, race, gender, faculty of study, residence status, school-level characteristics and infrastructure, school Apartheid classification, home language, grant recipient status, year of first registration at UCT, and year of matriculation included in specification, but not reported; Gender categories for transgender and unclassified are included, however, due to small sample size, point estimates of the effects have been omitted to avoid confusion.

Table 17: Robustness check 2: IEB effects from various regression specifications, individual NBT scores included

| Specification | Model C | Model C non-IEB | Former Col/Ind (IEB) | Former Col/Ind | Post-Apartheid IEB | Post-Apartheid (non-IEB) | Independent schools | N |
|---|---|---|---|---|---|---|---|---|
| Pooled OLS | 2.167*** | 0.800 | 5.428*** | 1.155 | 6.477*** | 0.580 | 1.729*** | 5,462 |
| | (0.748) | (0.508) | (1.513) | (0.936) | (1.043) | (1.375) | (0.662) | |
| **Faculty Regressions** | | | | | | | | |
| COM | 2.765** | 1.138 | 6.323*** | 2.436 | 6.644*** | -0.808 | 3.440*** | 1,847 |
| | (1.340) | (0.906) | (2.210) | (1.956) | (1.901) | (2.300) | (1.120) | |
| EBE | 3.257** | 2.085** | 7.163*** | 2.119 | 8.764*** | -2.940 | 2.921** | 1,087 |
| | (1.489) | (1.007) | (2.264) | (1.803) | (1.936) | (4.135) | (1.343) | |
| HUM | 0.717 | 0.742 | 1.569 | 0.004 | 7.631*** | 5.049 | -0.918 | 1,047 |
| | (1.929) | (1.380) | (5.443) | (2.269) | (2.448) | (3.498) | (1.773) | |
| LAW | -10.304* | -16.857*** | - | -14.986*** | -28.459** | - | -0.848 | 74 |
| | (5.679) | (4.229) | | (4.579) | (11.336) | | (6.222) | |
| MED | 3.581** | 0.615 | - | 0.956 | 4.506 | -0.633 | 2.239 | 727 |
| | (1.715) | (1.083) | | (1.847) | (2.739) | (2.158) | (1.732) | |
| SCI | 1.980 | -1.559 | 6.590* | 2.572 | 2.400 | 5.851 | -0.274 | 680 |
| | (2.357) | (1.754) | (3.509) | (2.392) | (3.149) | (3.964) | (2.460) | |
| **Quantile regression** | | | | | | | | |
| q10 | 3.936** | 2.956** | 10.933*** | 1.717 | 7.417*** | 1.804 | 3.082*** | 5462 |
| | (1.786) | (1.160) | (3.696) | (1.973) | (2.327) | (1.989) | (1.158) | |
| q25 | 2.252* | 0.822 | 6.895*** | 1.575 | 7.512*** | -1.047 | 1.758* | 5462 |
| | (1.323) | (0.881) | (2.658) | (1.363) | (2.636) | (1.968) | (1.018) | |
| q50 | 1.790*** | 0.103 | 3.588** | 0.506 | 6.202*** | 0.083 | 1.706*** | 5462 |
| | (0.610) | (0.500) | (1.413) | (0.870) | (1.156) | (1.375) | (0.579) | |
| q75 | 0.592 | -0.164 | 1.076 | 0.921 | 4.252*** | 0.558 | 1.318** | 5462 |
| | (0.632) | (0.467) | (2.568) | (1.080) | (0.682) | (1.257) | (0.546) | |
| q90 | 1.226 | 0.060 | 0.722 | 1.243 | 4.805*** | 4.461* | 0.849 | 5462 |
| | (0.847) | (0.619) | (2.970) | (0.911) | (1.510) | (2.408) | (0.915) | |
| Probit ME | 0.060** | 0.043*** | - | 0.039 | 0.107*** | -0.008 | 0.056*** | 5469 |
| | (0.024) | (0.016) | | (0.024) | (0.024) | (0.048) | (0.020) | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Ordered Probit ME** | | | | | | | | |
| First class | 0.043*** | 0.012 | 0.112* | 0.016 | 0.139*** | -0.002 | 0.047*** | 5511 |
| | (0.016) | (0.009) | (0.058) | (0.016) | (0.031) | (0.024) | (0.013) | |
| Upper second | 0.020*** | 0.006 | 0.042*** | 0.008 | 0.048*** | -0.001 | 0.021*** | 5511 |
| | (0.007) | (0.005) | (0.015) | (0.008) | (0.008) | (0.012) | (0.006) | |
| Lower second | 0.006** | 0.003 | -0.005 | 0.004 | -0.012 | -0.000 | 0.006** | 5511 |
| | (0.002) | (0.002) | (0.015) | (0.003) | (0.010) | (0.007) | (0.002) | |
| Third class | -0.030*** | -0.008 | -0.073** | -0.012 | -0.088*** | 0.001 | -0.033*** | 5511 |
| | (0.011) | (0.006) | (0.033) | (0.011) | (0.017) | (0.017) | (0.009) | |
| Fail | -0.038*** | -0.012 | -0.076*** | -0.016 | -0.086*** | 0.002 | -0.041*** | 5511 |
| | (0.013) | (0.009) | (0.025) | (0.015) | (0.014) | (0.026) | (0.011) | |

Source: UCT student records data (2018), Department of Basic Education (2018), and Human Science Research Council (2000).
Note: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentheses; Controls for parents' education level, grandparents' education level, matric average, indicator of whether a student took pure mathematics at school, race, gender, faculty of study, individual NBT scores, residence status, school-level characteristics and infrastructure, school Apartheid classification, home language, grant recipient status, year of first registration at UCT, and year of matriculation included in specification, but not reported; Gender categories for transgender and unclassified are included, however, due to small sample size, point estimates of the effects have been omitted to avoid confusion.