PERCEIVED RETURNS TO MATHEMATICS AND STUDENT ACHIEVEMENT: THE SOUTH AFRICAN CASE

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Abstract

This study investigates the relationship between students' perceived returns to mathematics – the future benefits a student believes they will obtain from studying mathematics – and mathematics achievement in South Africa. The study expands the scarce literature on the role of non-cognitive skills (and specifically extrinsic motivation) in education in South Africa. The 2019 Trends in International Mathematics and Science Study (TIMSS) South Africa dataset was used to perform Ordinary Least Squares (OLS), Instrumental Variable (IV), and Fixed Effects (FE) estimations of the model. The study finds that perceived returns to mathematics has a positive and statistically significant relationship with mathematics achievement. Further, it was found that the positive relationship that intrinsic motivation has with mathematics achievement is increased when perceived returns to mathematics is high, but that students with low intrinsic motivation for mathematics do not perform significantly differently when their perceived returns to mathematics is higher. This provides important insight into the interaction between different types of cognitive skills. Additionally, high perceived returns to mathematics had a large and significant positive relationship with mathematics achievement for students in rural schools, and the positive relationship between perceived returns to mathematics and mathematics achievement shrunk as one progressed to a more urban school location. This shows that perceived returns to mathematics matter more for students in challenging circumstances, but, importantly, the study finds that students with high perceived returns to mathematics in rural schools still perform worse than students with low perceived returns to mathematics in urban schools. This is an important finding in the South African context where gross inequalities in education persist: non-cognitive skills are important for educational achievement, but more needs to be done to improve the functionality of poor schools in South Africa.

1. Introduction

Education is widely recognised as one of the key inputs to the developmental process of an economy (Psacharopoulos & Woodhall, 1985). South Africa is a country fraught with the socioeconomic issues of poverty and inequality, and improving education outcomes is one of the key goals of the National Planning Commission's (NPC) National Development Plan (NDP) for reducing inequality and eliminating poverty in South Africa by the year 2030 (National Planning Commission, 2012). Despite the government's acknowledgement and focus on the importance of education for the development of the South African economy, education outcomes in South Africa remain poor, with South Africa ranking near the bottom of international education quality assessments such as the Trends in International Mathematics and Science Study (TIMSS) (Juan et al., 2019) and the Southern and Eastern African Consortium for Monitoring Educational Quality (SACMEQ). These studies found that South Africa performs poorly in mathematics and literacy in comparison even to surrounding African countries with much lower levels of GDP per capita and spending on mathematics and literacy (Van der Berg et al., 2011). Therefore, investigation into the factors that improve education quality is an important research area in development economics, as improving education quality is one of the cornerstones of the development of the South African economy.

In evaluating the inputs that lead to education outputs in South Africa, the focus in the local education economics sphere has been on classroom, school, and broader institutional factors that affect academic performance (Hofmeyr, 2022). Investigation into the effect of non-cognitive skills such as mood, attitudes, motivation, and social skills on academic performance in South Africa has been scarce, despite the growing international recognition of the importance of non-cognitive skills for academic performance, making them an important input into the education production function (Hofmeyr, 2022). The studies of the effects of non-cognitive skills on academic performance have largely taken place in the high-income country context, thus, the generalisation of these results to the South African education context, with its high levels of inequality, may not be possible.

In this research report, I study South African students' perceived returns to mathematics and its association with academic achievement at the Grade 9 level. The construct of "perceived returns" in this context refers to the future benefits to studying mathematics that students believe they will receive, such as returns in the job market, access to opportunities in the higher education sphere, and benefits in everyday life. This investigation falls under the realm of non-cognitive skills, specifically under the domain of motivation. Motivation can be further divided into intrinsic motivation – doing an activity for the inherent satisfaction of the activity itself – and extrinsic motivation – doing an activity to gain some separable outcome (Ryan & Deci, 2000). Perceived returns falls under the extrinsic type of motivation.

In the sparse literature on non-cognitive skills and academic achievement in South Africa, the relationship between motivation and academic achievement has been investigated at the university student level by Sikhwari (2014) and Pleace & Nicholls (2022), with one working paper from Stellenbosch University investigating motivation at the school level using the 2015 TIMSS data set (Fourie & Shepherd, 2019). Given the increasing global recognition of the importance of non-cognitive skills in the education production process, my study of the relationship of perceived returns and student achievement provides a contribution to the sparse South African literature.

In this study, I pose the following main question:

What relationship does a student's perceived returns to mathematics have with their mathematics achievement?

As an extension of this broader question, I also ask the following sub-questions to obtain a richer understanding of the relationship of perceived returns with academic performance in South Africa:

(1) Does the relationship between perceived returns to mathematics and mathematical achievement vary along the distribution of intrinsic motivation? In other words, if a student is not intrinsically motivated to study mathematics out of inherent interest, can perceived returns to mathematics extrinsically motivate this student to put forth the effort to achieve higher grades in mathematics?

(2) Does the relationship between perceived returns to mathematics and mathematical achievement vary along the school socio-economic status distribution? In other words, can extrinsic motivation in the form of perceived returns to mathematics overcome the disadvantage of resource scarcity in the school? Or does the interaction of school resources and non-cognitive skills produce larger increases in educational output?

To answer these questions, I use the South African Trends in International Mathematics and Science Study (TIMSS) 2019 dataset to estimate the relationship between perceived returns to mathematics and mathematics achievement using Ordinary Least Squares (OLS), Instrumental

Variable (IV) and Fixed Effect (FE) techniques. A more detailed description of the data used and the methodology employed is provided in section 3.

The research report proceeds as follows: Section 2 presents the literature review, which guides the formulation of my hypotheses. Section 3 details the dataset and the methodology employed. Section 4 presents the results of the analyses and the discussion of the results, and Section 5 concludes.

2. Literature Review

In this section, the relevant international and South African literature will be reviewed to form the hypotheses surrounding non-cognitive skills, and more specifically, perceived returns to mathematics and its relationship with student achievement in mathematics. Further, the literature surrounding other factors that affect educational achievement outside of non-cognitive skills shall be reviewed in order to inform the specification of the econometric models to test the relationships between the variables of interest. The construction of the econometric models will mainly be informed by the South African education literature to develop the model most appropriate for the unique South African context.

2.1 Brief Overview of Education in South Africa

Much like the inequalities in income and wealth present in modern day South Africa, with its roots firmly tied to the devastating racial segregation policies of the apartheid system, there are large inequalities present in education in South Africa. It has been well established in cross-disciplinary literature that there are two distinct schooling systems in South Africa, a functional schooling system serving an elite minority, and a dysfunctional schooling system serving the vast majority of the population (Spaull, 2019).

As with the inequalities in income and wealth in South Africa, the inequalities in education stem from the legacy of apartheid policies. Schooling under the apartheid regime was designed to build the human capital of the minority white race group, while at the same time dismantling the education of all other race groups, systematically excluding them from realising their academic potential (Seekings & Nattrass, 2008).

An example of the exclusion of non-white race groups from education opportunities can be seen in the Bantu Self Governing Act of 1959 where Africans were systematically removed from "white" urban and suburban areas and transferred to "Bantustans", the so-called homelands, and offered "independence" but with this independence came lack of funding and support from the then apartheid government. Teacher training colleges and other such institutions in these Bantustans were severely underfunded and under-resourced (Chrisholm, 2012). The inequality in resourcing of teachers and schools between the "white" schools in the urban and suburban centres of the country and the schools catering to the rest of the race groups on the periphery created the two schooling-system position which South Africa finds itself in today.

In the post-apartheid era, the presence of the two-tiered education system remains. The former Bantustans remain some of the poorest areas in the country, with new generations continuing to receive the sub-par education on offer in these locations (Chrisholm, 2012). Access to quality education remains segregated by class, with the delineation no longer being along racial lines but by the lines of wealth. In 2018, the top 200 high schools in South Africa produced more distinctions (the highest category of student achievement in South Africa) for mathematics in grade 12 than the other 6600 schools combined, which, in percentage terms, means that the top 3% of schools produced more distinctions than the other 97% combined. Within these 200 schools, 175 of them charge significant school fees (Spaull, 2019). These fee-charging schools are mostly previously white only ("model C") schools that received targeted government funding and resourcing under the apartheid government regime. In the post-apartheid era, in order to keep these schools in the public domain, the ANC led democratic government allowed these schools to operate mostly unchanged with the exception that they could charge fees (Spaull, 2019). Thus, learners of all races can now attend high quality schools, so long as they can afford to pay the school fees.

2.2 Non-Cognitive Skills and Academic Achievement

As stated in the introduction, the inputs of education production functions in the South African education economics sphere have mainly examined factors that relate to the classroom, school, and the wider community as inputs that produce educational outputs, and scarce research has been done in the area of non-cognitive skills as inputs to the education production function (Hofmeyr, 2022). Internationally, the importance of non-cognitive skills has received wide-spread attention, with the study of areas such as mood, motivation and perseverance becoming increasingly prevalent.

Heckman (2006) has been a forerunner in the economics field, highlighting the importance of non-cognitive skills in education and for success in other spheres of life. Heckman (2006) details the results of the Perry Preschool program, an intervention targeted at improving the education outcomes of previously disadvantaged African American children. The treatment group in the intervention received significantly higher test scores than those in the control group despite there being no significant difference in IQ level between the two groups. This was due to the treatment group being more motivated to learn than their peers in the control group. Furthermore, the treatment and control groups showed significant differences later in life – those in the treatment group showed higher school completion and employment rates, house ownership rates and lower rates of arrest.

Garcia (2014) finds that the development of strong positive non-cognitive skills fosters individual and wider societal benefits, such as better mathematics and reading skills and better performance in the workplace. Garcia (2014) further emphasises that non-cognitive skills can be moulded by external factors, such as experiences in the classroom, and calls for the development of non-cognitive skills to become an explicit goal in the construction of education policy.

A 2015 OECD report finds that the importance of non-cognitive skills in education has begun to be widely recognised internationally and governments from across the OECD have begun to include the development of non-cognitive skills such as autonomy, intercultural tolerance, and responsibility as explicit education policy goals (OECD, 2015 pp. 95-105).

As mentioned earlier, these studies have all been conducted in the high-income country context. Hofmeyr (2022) provides a summary of the main findings of the study of non-cognitive skills that are consistent in the high-income country context: (1) Non-cognitive skills are strong predictors of high school completion rates and high school performance; (2) There is a large positive association between conscientiousness (the quality of wanting to perform your duty excellently) and academic achievement that is largely independent from cognitive skill (in other words, the relationship remains even when cognitive skill is controlled for); (3) Many non-cognitive skills are developed in the early years of life, with the social contexts of the home playing a key role in the development of non-cognitive skill; and (4) Non-cognitive skill can be developed in later stages of life through targeted interventions.

While these findings are interesting and have important lessons attached to them, one must be cautious when generalising them to the context of a highly unequal developing country such as South Africa. The exploration of non-cognitive skill and its relationship with performance in the school and workplace has only recently begun to pick up, with a handful of studies investigating these relationships. Sikhwari (2014), Mason (2018) and Pleace and Nicholls

(2021) have conducted studies into the relationships between non-cognitive skills and academic performance at the university level in South Africa.

Sikhwari (2014) used a simple random sample of second year students across four schools of a university in South Africa's Limpopo province to study the relationship between the non-cognitive skills of motivation and self-concept (the self-constructed beliefs one has about oneself) and academic performance, measured through the examination results of the participants in the study. The author found strong positive relationships between motivation, self-concept, and academic achievement.

Mason (2018) and Pleace and Nicholls (2022) investigated the relationship between grit (the sustained pursuit and passion for a long-term goal in the face of adversity) and academic performance in first-year student cohorts of two separate South African universities. Both studies find positive relationships between grit and academic performance, with students who possessed a high level of grit performing significantly better than students with a low level of grit. Pleace and Nicholls (2022) further found that motivation was not a significant direct predictor of academic performance, but that intrinsic motivation was significantly correlated with grit – students with high levels of intrinsic motivation persevered more in the face of adversity.

Wills and Hofmeyr (2019) and Hofmeyr (2020) investigate the relationship between grit and academic performance in poorly resourced, disadvantaged and high poverty schools in South Africa. Wills and Hofmeyr (2019) find that students who positively persevere when faced with hardship perform significantly better academically. Hofmeyr (2020) finds significant positive associations between grit and student achievement, but that there is a larger return to grit for students in more functional schools that have access to better resources, showing that non-cognitive skills interact with other inputs in the education production function to produce educational outputs. A 2019 working paper by Fourie and Shepherd finds positive associations between extrinsic motivation and academic performance in the grade 9 South African cohort using the 2015 TIMSS South Africa data set.

Under the scope of non-cognitive skills, motivation is a skill that has received more attention in the field of psychology but is recently receiving attention in education economics. As stated in the introduction, motivation can be broadly divided into intrinsic (acting out of inherent satisfaction of performing the action) and extrinsic (acting to obtain some separable outcome) motivation. Intrinsic motivation has often been found to be associated with greater positive returns to academic performance, with students exhibiting intrinsic motivation performing significantly better than students exhibiting extrinsic motivation, and extrinsic motivation has at times been found to be negatively associated with other non-cognitive skills that lead to academic performance, such as perseverance (Karlen et al., 2019).

Autonomy in education – the feeling that you are learning out of your own choice rather than under the control of another person – has generally been associated with better academic achievement (Ryan & Deci, 2000). Ryan and Deci (2000) highlight an issue prevalent in the discussion and research of extrinsic motivation: extrinsic motivation is often viewed as a non-autonomous form of motivation, but in reality, extrinsic motivation exists on a spectrum of autonomy. An example provided by the authors clearly illustrates this point: a student can do their homework because they can see the value that the homework has for their future career advancement, or a student can do their homework simply because their parents tell them to. Both scenarios provide examples of extrinsic motivation, as the student is not doing their homework due to the inherent satisfaction it brings them, but the two scenarios vary widely in autonomy – with the first scenario presenting a student acting with greater autonomy, feelings of control and personal endorsement, and the second scenario presenting a student acting out of conformity with the external command of their parents. The authors note that, with the varying types of extrinsic motivation, come varying outcomes to education. Students who exhibit more autonomous forms of extrinsic motivation generally enjoy school more, form better coping habits and put forth more effort in school than their counterparts who are less autonomously extrinsically motivated – often showing decreasing interest and effort in school as well as negative coping habits such as disowning responsibility for negative performance (blaming the teacher etc).

Ryan and Deci (2000) divide extrinsic motivation into four categories: external regulation, introjected regulation, identified regulation, and integrated regulation. These categories increase in level of autonomy, with the perceived locus of causality becoming more internal as one progresses through the respective categories. Under external regulation, the locus of causality is external, and actions are performed to satisfy external demands or rewards. Introjected regulation involves the taking in of a regulation but not completely accepting it as one's own, and actions are performed to avoid guilt. Identified regulation is more autonomous and involves the conscious valuation of a goal or behaviour and accepting it as personally important, and the final type of extrinsic motivation – integrated regulation – occurring when identified regulations are fully assimilated into oneself and align with all other personal values and needs.

Zhao et al. (2018) found in their study of Chinese schools that students who exhibited intrinsic motivation and students who were more autonomously extrinsically motivated possessed higher levels of grit and a "growth mindset", whereas students who were less autonomously extrinsically motivated, i.e., through external regulation, showed lower levels of grit and did not exhibit a growth mindset. This appears to contradict the findings of Karlen et al. (2019) mentioned earlier (who found that extrinsic motivation was negatively correlated with other non-cognitive skills that lead to academic performance) and highlights the important issue raised by Ryan and Deci (2000): different types of extrinsic motivation have different associations with academic performance. The extrinsic motivation construct in the study of Karlen et al. (2019) consisted of externally regulated (less autonomous) motivation as opposed to self-determined, internally regulated (more autonomous) extrinsic motivators. Thus, when studying extrinsic motivation and its association with academic performance, one must be careful to be specific on where the locus of control of the student lies, and not to use "extrinsic motivation" as an umbrella term.

It has been established that intrinsic motivation trumps extrinsic motivation in its association with academic performance, but, as Reeve (2009) points out, not all tasks a student is required to perform will be inherently interesting to them. This is where extrinsic motivation is of great importance. Reeve (2009) explains that, despite uninteresting homework assignments and other unsatisfying activities such as rule-following being a necessity, teachers can play a role in instilling an autonomous mode of extrinsic motivation in their students by providing explanatory rationales for uninteresting activities. Providing these rationales can make students see the value in performing these tasks and why the costs are worth the benefit, and can externally transform these tasks into something that the students find personal value in (Reeve, 2009).

2.3 Other Factors that Affect Education Outcomes

It is important to review factors that have consistently been shown to affect educational outcomes in South Africa outside of non-cognitive skills to be able to specify an econometric model suitable for the South African context.

As expressed in the articles by Seekings and Natrass (2008), Chrisholm (2012) and Spaull (2019) reviewed earlier, the functionality of schools in modern day South Africa is largely a product of apartheid policies, with functional schools serving the wealthiest classes mainly located in the urban centres and suburban surrounds, and the dysfunctional schools concentrated mainly in the rural areas of South Africa. Rural occupation is mainly a consequence of systematic dispossession of non-white racial groups under apartheid policies (Hlalele, 2014). Characteristics of the rural setting in South Africa include poverty, long distances to towns and schools coupled with poor roads and infrastructure, limited access to information and communications technology (ICT), and limited access to services and amenities such as education and healthcare services and running water and electricity. The available schools further suffer from underqualified teachers, multigrade teaching in the same classroom with high student to teacher ratios (which has been shown to be negatively associated with academic performance - see Case & Deaton (1999) and Howie (2007)), poor teaching and learning conditions with a lack of appropriate resources, and competing priorities between domestic chores and education among students (Hlalele, 2014).

In addition to the location of the school, the schooling environment also matters. International literature shows that victims of bullying in schools show significantly lower levels of psychological and physical wellbeing (Rigby, 2003), as well as significantly lower levels of academic achievement (Juvonen et al., 2010). The relationship remains the same in South Africa, with victims of bullying at school performing worse academically and being more likely to drop out of school (Townsend, et al., 2008).

Several studies relay the importance of teacher accountability in producing positive educational outcomes (see Spaull (2015). This is problematic in South Africa as teacher accountability structures are relatively weak (van der Berg et al., 2011) with Spaull (2015: 137) noting that the "…lack of accountability for student learning outcomes in South Africa is arguably one of the major impediments to quality education for the poor." An important consideration, though, is teacher's knowledge capacity, as low teacher content knowledge in subjects such as mathematics is a prevalent binding constraint to the attainment of education in South Africa. This results in a two-tiered accountability issue: accountability without capacity (you cannot be held accountable for what you do not know) and capacity without accountability (Spaull, 2015). Solving this problem is a complex political issue with politically influential South African teachers' unions vehemently opposing and overturning any teacher accountability systems implemented by government (van der Berg et al., 2011).

While the school and classroom play important roles in the shaping of educational outcomes, the home context plays a vital role in determining academic success. Parental involvement in their child's education is an important determinant of educational outcomes. Fehrmann et al. (1987) finds that direct parental involvement has strong positive associations with school grades, with Ho Sui-Chu and Williams (1996) finding that parental discussion of academic activities in the home has a strong positive relationship with academic achievement. The vast inequalities in income and wealth in South Africa are highly correlated with parental education. More highly educated parents can provide better home resources for learning, and socioeconomic status (SES) shows strong positive relationships with educational attainment. In addition, more highly educated parents can be more effectively involved in the education of their children as they have greater capacity to assist with homework and other educational areas their child might be struggling with (Taylor & Yu, 2009).

The importance of being educated in your home language has been widely recognised in the literature internationally (Liddicoat, 2014) and learning problems tend to develop when children are not taught in the language that they speak at home (Gordon & Harvey, 2019). Chalmers (2019) shows that educating a child in their home language results in deeper understanding of the content, and that knowledge learned in the home language is easier to transfer to other languages. The literature shows that students who do better in school are often age appropriate for their grade, and the poor performance of older students can be attributed to the repetition effect – students who are older than their peers are often students who are repeating the grade as they have not grasped the fundamental concepts being taught in class (Zulu & Visser, 2018).

Clearly, the production of education outcomes is a complex system of inputs and institutional and structural processes, and care must be taken to capture this complexity when designing econometric models to reliably test the relationships between the variables of interest.

2.4 Contribution of this Study and Hypotheses to be Tested

As stated earlier, the South African literature on non-cognitive skills, and more specifically motivation, and the role it plays in fostering academic achievement is quite scarce, with most studies being conducted at the university level. The working paper by Fourie and Shepherd (2019) provides an insight into the role of extrinsic motivation and its association with academic achievement at the school level using the 2015 TIMSS South Africa dataset.

An important point raised in the literature review is that extrinsic motivation exists on a spectrum of autonomy – where the locus of control becomes more internal as one progresses along the spectrum – and that one should be specific when using the term "extrinsic motivation" as different types of extrinsic motivation have different relationships with academic achievement. In the study by Fourie and Shepherd (2019), the authors include in the construction of their extrinsic motivation variable student responses to statements regarding their parents' opinion on mathematics, where the locus of control is external. The variable of interest in this study – perceived returns to mathematics – is constructed from student perceptions of the future value that studying mathematics will provide them in different spheres of life – thus the origin of this form of motivation is internal to the student. Perceived returns to mathematics, therefore, lies on the more autonomous side of the motivation spectrum.

This study thus makes an important contribution to the study of extrinsic motivation in education in South Africa, as, stated earlier, students who exhibit more autonomous forms of extrinsic motivation generally put forth more effort in class and have a more positive schooling experience (Ryan & Deci, 2000). As referenced earlier, the study of Hofmeyr (2022) finds that non-cognitive skills can be developed through targeted interventions, and Reeve (2009) finds that teachers can play a role in instilling autonomous modes of extrinsic motivation in their students.

This study asks important sub questions, such as whether perceived returns matters when a student is not intrinsically motivated to study mathematics, or when a student attends a school faced with significant resource constraints. If this study finds that students' perceived returns to mathematics is positively related with academic performance, and that this relationship holds at different levels of intrinsic motivation and socioeconomic status, this has important implications for the teaching of mathematics in South Africa.

This study makes further contributions by using the more recent results of the TIMSS South Africa study, as well as employing Instrumental Variable and Fixed Effect techniques to account for possible endogeneity in estimations. The methodology will be explained in more detail in the section to follow.

After reviewing the local and international literature, I have conceptualised the following hypotheses:

(1) Students with higher levels of perceived returns to mathematics will perform better in mathematics, *ceteris paribus*.

The local and international literature raise the importance of non-cognitive skills in determining education outcomes, with the studies of Ryan and Deci (2000), Reeve (2009) and Zhao (2018) showing that autonomous, self-determined forms of extrinsic motivation are associated with improved academic outcomes.

(2) Students with high levels of intrinsic motivation and high perceived returns to mathematics will perform better than students only exhibiting high intrinsic motivation, who will perform better than students exhibiting only high perceived returns to mathematics, who will in turn perform better than students lacking both intrinsic motivation and high perceived returns to mathematics, *ceteris paribus.*

The studies of Karlen et al. (2019) show that intrinsic motivation is associated with higher performance than extrinsic motivation.

(3) Students with high perceived returns to mathematics in functional, better-resourced schools will perform better than students with high perceived returns to mathematics in less functional, less resourced schools in South Africa, *ceteris paribus.*

The study of Hofmeyr (2021) shows a significant effect of the interaction between non-cognitive skills and school functionality and resource endowment in South Africa.

3. Data and Methodology

In this section I will be describing the data set as well as the econometric methodology I will be using to test my hypotheses and answer my research questions.

3.1 Data

To answer the research questions posed in Section 1 and to test the hypotheses proposed in Section 2, a data set that provides adequate information on student performance as well as student, school, and home context data is required.

The 2019 Trends in International Mathematics and Science Study (TIMSS) will serve as the dataset for this study. TIMSS is an international assessment of mathematics and science education quality founded by the International Association for the Evaluation of Educational Achievement (IEA) and has been conducted every 4 years since its inception in 1995 (Mullis et al., 2020). This provides an international assessment of education quality spanning over two decades, as well as a means for assessing education quality across countries. In the 2019 round of the TIMSS study, 64 countries, including South Africa, participated, with South Africa being a participant in the TIMSS study since its inception.

The TIMSS study is conducted at the grade 5 and grade 9 level in South Africa and students in participating schools are subjected to standardised mathematics and science assessments, providing a measure of student achievement. Countries participating in the TIMSS study endorse the curriculum framework to ensure that students are being tested on content matching their required schooling learning outcomes. Students were tested on a wide array of mathematics and science content, and questions were asked in both multiple choice and open-ended format. In addition, the students, mathematics and science teachers, and principals of participating schools are required to complete questionnaires that provide information on student, classroom, school, and home background contexts, allowing investigation into how these factors affect educational achievement. The results of the 2019 TIMSS South Africa grade 9 mathematics assessment will serve as the outcome variable in this study, while the explanatory variables will be drawn from the responses to the student, teacher and principal context questionnaires.

TIMSS is one of the largest international education quality assessments and the results from TIMSS are used by governments to advise education policy. The TIMSS South Africa 2019 assessment was conducted on a nationally representative sample of 20 892 grade 9 students from 520 schools with 519 principals and 543 and 537 maths and science teachers respectively (timsssa, 2019). All the above attributes make TIMSS an appropriate data set with which to conduct the analyses. The data from the TIMSS 2019 study is freely available on their webpage (www.timss.org).

The TIMSS achievement scores are reported on a scale ranging from 0 to 1000, with a centre point of 500 located at the mean of the combined achievement distribution. The IEA delimitates the TIMSS achievement scores into four categories or "International Benchmarks" representing different levels of student achievement. These are "Advanced" for a score above 625, "High" for a score above 550, "Intermediate" for a score above 475, and "Low" for a score above 400 (Mullis et al., 2019). In the 2019 TIMSS mathematics assessment, the South African grade 9 cohort scored an average achievement score of 389. In other words, the average South African grade 9 student does not reach the "Low" achievement benchmark set out in the TIMSS study (Reddy, et al., 2022). To provide context about the level of achievement required to reach the low TIMSS achievement benchmark, the IEA describes a student achieving a TIMSS achievement score of 400 as a student who has "…some knowledge of whole numbers and basic graphs" (Mullis et al., 2019).

3.2 Methodology

To estimate the relationship between my variable of interest – perceived returns to mathematics – and mathematics achievement scores, econometric analyses will be used. The variable "perceived returns to mathematics" was constructed from student responses to five questions regarding their view of the value of mathematics in their lives. The perceived returns variable was constructed using Multiple Correspondence Analysis (MCA)[1], based on the students' degree of agreement with the following statements in the TIMSS South Africa 2019 student context questionnaire: (1) "I think mathematics will help me in my daily life.", (2) "I need to do well in mathematics to get into the university of my choice.", (3) "I need to do well in mathematics to get the job I want", (4) "It is important to learn about mathematics to get ahead in the world.", and (5) "Learning mathematics will give me more job opportunities when I am an adult." The response choices to the above statements ranged from "Disagree a lot" to "Agree a lot" on a four-level Likert-type scale. All scales were standardised to have a mean of zero and a standard deviation of 1.

The questions asked in the TIMSS mathematics (and science) assessments are drawn from a wider pool of questions, so no two students are assessed with the same test. TIMSS uses Item Response Theory (IRT)[2] to construct a series of five "plausible values" (PVs) – scores which "represent a range of abilities a student might reasonably have, given the student's item responses" (Wu, 2005). These represent the students' achievement level in mathematics. Regression analysis with PVs entails performing a regression analysis individually with each PV and averaging the obtained coefficients[3] (OECD, 2009). This can be done in Stata with the user written program developed by Kevin Macdonald (2008) designed specifically to be used with PISA, TIMSS and PIRLS student achievement data sets as well as the Programme for the International Assessment of Adult Competencies (PIAAC) dataset.

[1] Multiple Correspondence Analysis (MCA) is a dimensionality reduction technique that allows for the analysis of the patterns of relationships of categorical variables (Abdi & Valentin, 2007). MCA allows for the representation of latent structures of multiple categorical variables in a lower dimensional space.
[2] Item Response Theory (IRT) is a family of mathematical models which examine the underlying difficulty of questions and TIMSS uses IRT to assign students the series of five PVs which are comparable across all students.
[3] The calculation of standard errors to determine levels of significance is a more complicated process, details of which can be found in the OECD Library (OECD, 2009).

However, due to the limited functionality of the package for postestimation analysis and more advanced econometric modelling, as well as prior precedent showing that estimation using the first plausible value typically recovers population parameters (Wu (2005)), estimations in this study will be performed using the first plausible value of the student mathematics score as the outcome variable, as has frequently been done in other research using the TIMSS data set (see Gustafsson et al., (2016) and Lorah (2018) for example). Nonetheless, to test the validity of this decision, I also used the plausible values regression method for all the models estimated in this paper which the PV command in Stata supports. Reassuringly, the results of the estimations were not significantly different from the results of the estimation done with the first plausible value only. These robustness checks will be discussed later in the results section.

To test the three hypotheses stated earlier, I will initially estimate the relationships of interest using Ordinary Least Squares (OLS) regression to establish a baseline upon which the estimation can be refined. All estimations are weighted by the student sampling weights to ensure the contribution of each student to the estimation of population parameters is as if a national census was conducted[4]. To test the first hypothesis and answer the main research question, the following OLS regression model will be estimated to establish the relationship between the students' perceived returns to mathematics and mathematics achievement:

$$mscore_i = a_0 + \beta_1 PR_i + \gamma X_i + s_j + t_k + a_i + \epsilon_i \quad (1)$$

where $mscore_i$ represents the students' mathematics assessment score (using the first plausible value as explained above), a_0 represents the intercept, PR_i represents the students' level of perceived returns to mathematics with β_1 being the coefficient of interest. X_i represents a vector of student, school, and home covariates (which are included in stages in the actual regression estimations). s_j, t_k, and a_i represent unobservable fixed effects of school j, teacher k and student i respectively. ϵ_i represents the error term.

Included in X_i are intrinsic motivation for mathematics, school location variables, school safety and bullying scales, class size, teacher accountability scales, parental involvement in mathematics, books in the home, home socio-economic status, the frequency the student speaks the test language at home, student sex and student age. This equation resembles the typical education production function approach commonly estimated in the education literature

[4] For more information on the TIMSS sampling methods, see the TIMSS technical report (Martin et al., 2020).

(Hanushek in Bradley and Green, 2020, p. 161). The output of the education production function is typically some measure of student achievement (TIMSS mathematics achievement scores in this study) and this is related to inputs, both those which can be directly influenced by policymakers such as curricula, and characteristics of schools and teachers, and other inputs which cannot be directly controlled by policy such as family, friends, and learning capacities of students (Hanushek in Bradley and Green, 2020). The definition and construction of these variables was informed by the review of the literature, the details of which are shown in Table 1.

To test the second hypothesis, that students with high intrinsic motivation for mathematics as well as high perceived returns will perform better than students with only intrinsic motivation or perceived returns, the following OLS regression shall be run:

$$mscore_i = a_0 + \beta_1 PR_i + \beta_2 intrinsic_i + \beta_3 PR_i * intrinsic_i + \gamma X_i + s_j + t_k + a_i + \epsilon_i \quad (2)$$

where $intrinsic_i$ represents the level of intrinsic motivation student i has for mathematics and β_3 is the coefficient of the interaction between the students' perceived returns to mathematics and their intrinsic motivation for mathematics. The variable $intrinsic_i$ was constructed using MCA with student responses to the level of agreement with the following statements: (1) "I enjoy learning mathematics", (2) "I like mathematics", (3) "I like any schoolwork that involves numbers", (4) " I like to solve mathematics problems", and (5) "Mathematics is one of my favourite subjects". Including the interaction between perceived returns and intrinsic motivation, as well as the two variables individually allows for a deeper characterisation of the effects that perceived returns and intrinsic motivation have individually, as well as their role in jointly determining mathematics results.

Table 1: Construction of Explanatory Variables

Variable	Construction
Perceived returns to mathematics	MCA was used to construct the scale based on student responses to the degree that they agreed with the following statements: "I think mathematics will help me in my daily life.", "I need to do well in mathematics to get into the university of my choice.", "I need to do well in mathematics to get the job I want", "It is important to learn about mathematics to get ahead in the world.", and "Learning mathematics will give me more job opportunities when I am an adult.". The four response options ranged from "Disagree a lot" to "Agree a lot".
Perceived returns to science	MCA was used to construct the scale with student responses to the same statements above, but with relation to science.

Intrinsic motivation for mathematics	Students were asked their level of agreement with the statements: 1) "I enjoy learning mathematics", 2) "I wish I did not have to study mathematics", 3) "Mathematics is boring", 4) "I like mathematics" 5) "I like any schoolwork that involves numbers" and 6) "I like to solve mathematics problems". Four response options were available ranging from "Disagree a lot" to "Agree a lot" and statements (2) and (3) were reverse coded so that "Agree a lot" was the lowest category. The scale was constructed using MCA.
School location	School principals were asked which of the response options best described the immediate area in which the school was located. The response options were (1) Remote Rural, (2) Small Town or Village, (3) Medium City or Large Town, (4) Suburban, and (5) Urban. "Remote Rural" served as the omitted category in the analyses.
Students feel safe at school	Students were asked the extent to which they agree with the statement "I feel safe when I am at school" with the four response options ranging from "Disagree a lot" to "Agree a Lot". "Disagree a lot" served as the omitted category.
Bullying scale	The scale was created using MCA representing the severity of bullying which was measured through student responses to the frequency of 14 examples of bullying, covering physical, verbal, cyber, other forms of psychological bullying and damage to property. Response options ranged from "Never" to "At least once a week". A higher number on the scale represents more frequent bullying.
Mathematics class size	Teachers were asked how many students were in their class.
Teacher accountability	Principals were asked to what degree teachers "Arriving late or leaving early" and "Absenteeism" was a problem in the school with response options ranging from "Serious problem" to "Not a problem". The scale was constructed using MCA.
Parents think mathematics is important	Students were asked the degree to which they agreed with the statement "My parents think that it is important that I do well in mathematics" with the four response options ranging from "Disagree a lot" to "Agree a lot" with the former serving as the omitted category.
Books in home	Students were asked how many books there were in their home with the following response options: (1) None or very few (0-10 books) (2) Enough to fill one shelf (11–25 books), (3) Enough to fill one bookcase (26–100 books), (4) Enough to fill two bookcases (101–200 books), and (5) Enough to fill three or more bookcases (more than 200) with option 1 serving as the omitted variable.

Home SES	Students were asked yes/no questions about whether they had the following items in the home: A computer/tablet, their own study desk, their own room, an internet connection, their own mobile phone, a dictionary, electricity, running water and a hot water geyser. The scale was constructed using MCA.
Speaks test language at home	Students were asked the frequency which they spoke the test language at home with the four responses ranging from "Never" to Always" with the former serving as the omitted category.
Female student	Students were asked if they were a girl or a boy. A dichotomous variable was constructed in which "girl" was coded as a 1 and "boy" was coded as a 0.
Student age	Students were asked which month and year they were born, and their age was given as a number in the TIMSS data set.

To test the relationship between perceived returns, school resources and functionality, and student achievement as put forth in the third hypothesis, the following OLS regression will be estimated:

$$mscore_i = a_0 + \beta_1 PR_i + \beta_2 sclocat_i + \beta_3 PR_i * sclocat_i + \gamma X_i + s_j + t_k + a_i + \epsilon_i \quad (3)$$

where $sclocat_i$ represents a vector of dummy variables detailing the principals' response to the question "Which best describes the immediate area in which your school is located?" with the response options: rural, small town/village, medium city, suburban and urban, with the option "rural" serving as the omitted category in the regression – functioning as a proxy for a less functional, less resourced school[5]. The interaction between perceived returns and school location will allow for the examination of the relationship between these two factors in jointly determining mathematics scores, and particularly whether extrinsic motivation in the form of perceived returns can serve to mitigate the disadvantage of being in a school with a lower resource level.

The fixed effects s_j, t_k, and a_i in the three equations above are time-invariant, unobservable school, teacher, and student characteristics that are likely to affect student achievement, such

[5] In the TIMSS questionnaire there are a group of questions pertaining to the level of resources within the school from which it is possible to create a school resource index, but the effect of school resources on mathematics performance is insignificant due to its high correlation with home SES. To overcome this issue of collinearity, school location is used as a proxy for school resource level. Various sources in the literature review highlight the correlation between better school quality and resource endowment and a more urban school location (see Seekings and Natrass (2008), Chrisholm (2012) and Spaull (2019) for example).

as innate talent or skill in the case of the student, or a unique management style of the principal of a particular school for example. Performing an OLS regression without controlling for these fixed effects may produce biased estimates. One method of addressing the problem of unobserved heterogeneity is to exploit the fact that the science achievement scores for students are available and estimating a within-student, between-subjects fixed effects model (Kang, 2007) taking inspiration from panel data fixed effects estimation techniques. This method entails estimating the following regression:

$$mscore_i - sscore_i = \gamma + \beta_1(PR_i - SPR_i) + \beta_2(t_k - t_s) + (\epsilon_i - \epsilon_i^s) \quad (4)$$

Where γ represents the intercept, $sscore_i$ represents the students' science achievement score and SPR_i represents the students' perceived returns to science, constructed with student responses to the same questions used to construct the mathematics perceived returns variable, but with regards to science. t_s represents science teacher fixed effects and ϵ_i^s represents the error term resulting from the regression of science scores on observable characteristics. Due to the fact that the unobservable fixed effects will be invariant across the two subjects, the effect of these unobservable characteristics will be differenced out.

Unfortunately, due to the phrasing of the response items in the TIMSS questionnaire regarding perceived returns to mathematics and science, most students generally respond in a similar manner across these two subjects[6], thus making it difficult to exploit variation in perceived returns across mathematics and science to estimate equation 4 above.

Instead, to account for unobserved time-invariant characteristics as best as possible school and teacher fixed effects are controlled for. The following regression will be estimated following the methodology of Woessmann and West (2006):

$$mscore_i = a_0 + \beta_1 PR_i + \delta D_s + \eta D_t + \gamma X_i + s_j + t_k + a_i + \epsilon_i \quad (5)$$

where D_s and D_t represent vectors of school and teacher dummies respectively. The school and teacher dummies will control for school and teacher fixed effects and will be added to equations (1) and (2) above. These dummy variables will not be added to equation (3) above as they will be collinear with the school location parameters being estimated.

[6] As a simple illustration of this problem, I created a variable that measures the difference between the two indices for maths and science perceived returns for each student. The mean was only 0.018, suggesting low variation in responses between subjects.

Unfortunately, the above method cannot control for student fixed effects (as we only have one year of data on the student and the within-student between-subject estimation was not feasible). This is problematic because unobserved characteristics of the student (such as innate ability) could be correlated with both extrinsic motivation and mathematics scores. Further, it could be argued that extrinsic motivation, such as perceived returns, could potentially present endogeneity problems through the avenue of reverse causality: a student could do well in mathematics due to extrinsic motivation, but the student may be more motivated due to good performance in mathematics.

To address this issue and to further test how robust the results of the OLS estimations are, I will use instrumental variable (IV) estimation. I will use the students' perceived returns to science as an instrument for perceived return to mathematics. Perceived returns to science is expected to be highly correlated with perceived returns to mathematics, but the future value that a student expects to derive from studying science should have no direct bearing on the student's mathematics achievement, other than through its correlation with perceived returns to mathematics.

The summary statistics of the dependent and independent variables are presented in Table 2, with detailed information on the construction of the relevant scales already provided in Table 1. The sample for which non-missing data was available on both the dependent variable (mathematics scores) and the explanatory variables is 14 816 students.

Table 2: Summary Statistics of Dependent and Independent Variables of the Estimation Sample

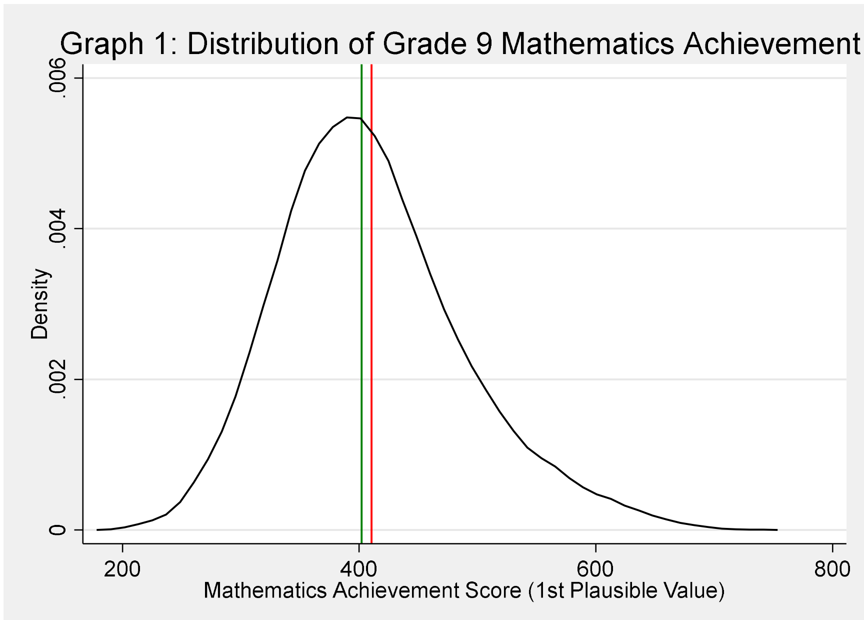
Variable	Obs	Mean	Std. Dev.	Min	Max
Math PV1	14816	410.336	78.698	188.078	743.717
Math PV2	14816	410.483	78.819	175.712	737.327
Math PV3	14816	409.382	79.448	162.220	786.116
Math PV4	14816	408.120	80.438	172.007	776.547
Math PV5	14816	409.367	79.878	187.056	755.130
Math perceived returns	14816	0.038	0.965	-4.682	0.677
Science perceived returns	14610	0.023	0.999	-3.233	0.883
Math intrinsic motivation	14816	0.005	1.004	-2.592	1.274
School level factors					
School location					
Remote rural	14816	0.202	0.401	0	1
Small town	14816	0.263	0.440	0	1
Medium City	14816	0.115	0.319	0	1

Suburban	14816	0.168	0.374	0	1
Urban	14816	0.253	0.435	0	1
Student feels safe at school					
Disagree a lot	14816	0.043	0.204	0	1
Disagree a little	14816	0.097	0.296	0	1
Agree a little	14816	0.327	0.469	0	1
Agree a lot	14816	0.533	0.499	0	1
Bullying scale	14816	-0.044	0.958	-1.293	3.127
Math class size	14816	47.323	16.599	3	118
Teacher accountability scale	14816	0.035	1.008	-2.502	1.299
Home level factors[7]					
Parents think mathematics is important					
Disagree a lot	14816	0.018	0.134	0	1
Disagree a little	14816	0.044	0.205	0	1
Agree a little	14816	0.194	0.396	0	1
Agree a lot	14816	0.744	0.437	0	1
Books in home					
0-10	14816	0.426	0.495	0	1
11-25	14816	0.370	0.483	0	1
26-100	14816	0.129	0.335	0	1
101-200	14816	0.042	0.200	0	1
>200	14816	0.033	0.178	0	1
Home SES scale	14816	0.081	1.571	-4.589	2.348
Other student level factors					
Speaks test language at home					
Never	14816	0.059	0.235	0	1
Sometimes	14816	0.590	0.492	0	1
Almost Always	14816	0.165	0.371	0	1
Always	14816	0.186	0.389	0	1
Student sex					
Boy	14816	0.458	0.498	0	1
Girl	14816	0.542	0.498	0	1
Student Age	14816	15.472	1.014	10.080	19

The mean level of achievement in the TIMSS 2019 mathematics assessment in the estimation sample is 410.34 (red line in Graph 1) with a standard deviation of 78.70, and a median is

[7] Parents level of education was not included in the model, as, even though this is identified as having positive returns to a students' academic achievement, it is highly collinear to home SES and loses significance once home SES is added to the estimations of the model.

402.19 as shown by the green line in Graph 1. The achievement scores range between 188.08 and 743.72. Graph 1 shows that the majority of the students in the estimation sample score less than the average, with the average score being skewed to the right by high-achieving students.



The pairwise correlations between the main independent variables of interest (perceived returns to mathematics, mathematical intrinsic motivation, and school location) and mathematics achievement are given in Table 3. There is a moderate positive relationship perceived returns to mathematics and mathematics intrinsic motivation and almost no correlation between the school location variables and the two other independent variables. There is a near-zero, positive correlation between perceived returns to mathematics and mathematics achievement, and the same relationship is observed between mathematics intrinsic motivation and mathematics achievement. There is a small positive correlation between attending school in a school location in a medium city, suburban and urban school location and mathematics achievement, with a small negative correlation present between rural and small town school locations and mathematics achievement.

Table 3: Pairwise Correlations Between the Main Variables of Interest

	Math Score (1st PV)	Math Perceived Returns	Math Intrinsic	Remote Rural	Small Town	Medium City	Suburban	Urban
Math Score (1st PV)	1.000							
Math Perceived Returns	0.060	1.000						
Math Intrinsic	0.036	0.411	1.000					
Remote Rural	-0.250	-0.007	0.090	1.000				
Small Town	-0.121	0.029	0.052	-0.300	1.000			
Medium City	0.115	-0.001	-0.022	-0.182	-0.216	1.000		
Suburban	0.179	-0.007	-0.077	-0.226	-0.268	-0.162	1.000	
Urban	0.115	-0.017	-0.062	-0.292	-0.347	-0.210	-0.261	1.000

3.3 Limitations of the Study

Of course, none of these methods are perfect in identifying causality. An ideal study would involve conducting a randomised control trial (RCT) where the mathematical performance of a treatment group whose teachers emphasise the future returns and value of studying mathematics, for example, could be compared to a control group. However, RCTs are expensive and have their own set of limitations. Therefore, there is still great value in working with TIMSS data as it contains a large random and nationally representative sample of students working within schools and is collected frequently and for countries across the globe in a standardised fashion.[8]

[8] It should also be noted that this study is being conducted on the grade 9 South African cohort and one should be careful when generalising these results to the rest of the child and adult student population. The international literature does show, however, that positive relationships between non-cognitive skills and performance in the academic and work world tend to hold across the age distribution (Kautz et al., 2014).

Instrumental Variable regression is used to address potential endogeneity problems in the OLS estimation. It is very difficult to find a perfect instrument and it could be argued that due to the similar nature of mathematics and science, students may conflate the perceived returns to these two subjects, making them impossible to separate. Perceived returns to a more unrelated subject such as English or History may serve as a better instrument, allowing for a more robust assessment of the relationship between differing levels of perceived returns across subjects and individual student achievement. This was not possible, however, as the TIMSS dataset only assesses student achievement in mathematics and science.

Another important limitation of all studies investigating non-cognitive skills is that concepts such as motivation are inherently difficult to measure and quantify. For example, the statements in the TIMSS student questionnaire used to formulate the perceived returns to mathematics and science variables are phrased in a way that most students would generally agree with[9] – most students would generally agree that mathematics is important for future job and school prospects. Thus, the perceived returns to mathematics and science variables might not completely capture the extent to which these perceived returns motivate students. Although the students may generally agree with these statements, thus score highly on the perceived returns to mathematics index, this may not advise researchers what the main source of a students' motivation is, i.e., when faced with adversity, what allows a student to persevere? Due to most students generally agreeing with the statements used to construct the perceived returns, the estimates provided by the econometric analysis would understate the effect of perceived returns as a source of motivation. (Indeed, this was the reason that models controlling for fixed effects using within-student, between-subject variation were not possible to estimate, as discussed above.)

This is very difficult to overcome in observational data. The ideal scenario would be to have test subjects undergo functional Magnetic Resonance Imaging (fMRI) scanning to determine where intrinsic and extrinsic motivation are activated in the brain by observing neural activity and overlay this with affinity for mathematics and mathematics performance. Of course, this is beyond the scope of most research in the field of education economics, and therefore research on non-cognitive skills using datasets like the TIMSS remains an important contribution. However, there may be room for improvement in the way the concepts such as extrinsic

[9] This is an issue in other large scale education assessment studies such as the Programme for International Student Assessment (PISA).

motivation are elicited from students in observational data in the form of better-designed questions. Some suggestions will be considered in the final discussion.

4. Results and Discussion

In this section I will present the results of the various estimations and discuss the findings pertaining to the main question and the two sub-questions.

4.1 Perceived Returns and Mathematics Performance

In this section, the I present and discuss the results from the main set of regressions, which test whether students with higher perceived returns to mathematics perform better than students with lower perceived returns to mathematics (as per Hypothesis 1 above).

Table 4 presents the results from the OLS regressions on the first plausible value, with the explanatory variables introduced in stages, with the final column showing the full specification as outlined in equation 1 above.[10] Column 1 contains the result of a regression of the mathematics score on perceived returns to mathematics, and Column 2 contains the results of a regression of the mathematics score on intrinsic motivation. Columns 3-5 progressively add school/classroom level factors, home level factors, and other student background factors respectively.

The coefficients on perceived returns to mathematics remain positive and statistically significant in each step of the progression, with the level of significance falling from the 1% to the 5% level in the final specification. Similarly, the coefficients on intrinsic motivation for mathematics remain positive and significant at the 1% level in each step of the progression. The size of the coefficients attached to perceived returns decrease steadily through each step of the progression, with the largest falls in size taking place when school and home level factors are added. This suggests that perceived returns, a form of extrinsic motivation, is correlated with, or susceptible to influence from, external factors, such as factors in the classroom and the household, supporting the findings of Reeve (2009) above. In contrast, the size of the coefficients attached to intrinsic motivation remain relatively stable, indicating that intrinsic motivation is less susceptible to external influence.

[10] As a robustness check, these regressions were also estimated using Plausible Values Regression (PVR). Appendix Table A1 contains the results, which show that there is no substantive difference when compared to the results in Table 3. This gives confidence that using OLS on the first plausible value is an acceptable strategy, as it offers greater functionality than the PV command in Stata.

The signs on the coefficients for the rest of the explanatory variables are as expected and support the findings in the international and South African literature reviewed above. Students in more urban, safer and more functional schools do significantly better at mathematics compared to students in more rural, unsafe, and dysfunctional schools, as seen by the positive coefficients attached to the school location variables (where rural schools is the omitted category), perceptions of school safety, and teacher accountability, and the negative coefficients on the bullying and class size variables.

As expected from reviewing the literature, students who come from a wealthier household background, and with parents who are involved in their education perform better than students who come from less wealthy households, and who have parents that are less involved in their education. Students who speak the language of the test at home more often perform significantly better, and older and female students perform significantly worse in mathematics.

Table 4: Multivariate Regression of the Relationship Between Perceived Returns to Mathematics and Mathematics Scores (OLS on First Plausible Value)

	(1)	(2)	(3)	(4)	(5)
Math perceived returns	10.04***		6.905***	3.010***	2.037**
	(1.373)		(1.049)	(1.001)	(0.966)
Math intrinsic motivation		4.355***	6.901***	7.108***	7.185***
		(1.291)	(0.942)	(0.870)	(0.830)
School location: Small town			13.59**	9.028*	7.043
			(5.923)	(5.084)	(4.735)
School location: Medium city			45.73***	32.77***	26.65***
			(10.21)	(8.447)	(7.579)
School location: Suburban			56.64***	43.55***	36.17***
			(8.865)	(7.752)	(6.706)
School location: Urban			47.66***	34.51***	28.65***
			(7.267)	(6.194)	(5.350)
Student feels safe at school: Disagree a little			24.43***	21.76***	17.50***
			(4.314)	(4.093)	(3.709)
Student feels safe at school: Agree a little			18.65***	17.90***	15.73***
			(3.657)	(3.354)	(2.917)
Student feels safe at school: Agree a lot			10.07**	9.384***	10.11***
			(3.921)	(3.441)	(2.996)
Bullying scale			-15.80***	-14.63***	-11.82***
			(0.880)	(0.811)	(0.802)
Math class size			-0.754***	-0.552***	-0.454***
			(0.156)	(0.130)	(0.122)
Teacher accountability			12.14***	10.02***	8.939***
			(2.421)	(2.177)	(1.956)
Parents think math is important: Disagree a little				29.43***	27.39***
				(5.285)	(5.174)
Parents think math is important: Agree a little				32.13***	30.74***
				(4.560)	(4.581)
Parents think math is important: Agree a lot				45.95***	39.82***
				(4.296)	(4.315)
Books in home: 11-25				-0.306	-1.963
				(1.684)	(1.588)
Books in home: 26-100				18.91***	12.83***
				(2.749)	(2.441)
Books in home: 101-200				32.33***	26.86***

				(4.914)	(4.428)
Books in home: >200				33.13***	28.22***
				(5.692)	(5.126)
Home SES				13.57***	9.552***
				(0.839)	(0.725)
Speaks test language at home: Sometimes					8.019**
					(3.303)
Speaks test language at home: Almost always					33.50***
					(4.007)
Speaks test language at home: Always					40.60***
					(4.803)
Female student					-5.757***
					(1.309)
Student age					-17.35***
					(1.010)
Constant	398.6***	398.6***	397.3***	350.1***	611.1***
	(2.943)	(3.021)	(10.23)	(10.62)	(22.98)
N	14816	14816	14816	14816	14816
R^2	0.016	0.003	0.260	0.324	0.401
School/classroom level factors	NO	NO	YES	YES	YES
Home level factors	NO	NO	NO	YES	YES
Other student-level factors	NO	NO	NO	NO	YES

Notes: * *p<0.10; *** *p<0.05;* *** *p<0.01.* Cluster-robust standard errors in parentheses.

The results shown in Table 4 support the hypothesised relationship between perceived returns to mathematics and mathematical achievement: students who have a higher perceived returns to mathematics do significantly better than students who have a lower perceived returns to mathematics, controlling for intrinsic motivation and a range of other school, home and student factors.

To test how robust the results found using OLS regression are, instrumental variable estimation and controls for school and teacher fixed effects are added to the model, and the results are shown in Table 5. For ease of comparison, Column 1 reproduces the results of the OLS regression of mathematics score on perceived returns to mathematics including the full set of controls (as in Column 5 of Table 4). Column 2 shows the results of the two-stage least-squares (2sls) IV estimation, where perceived returns to mathematics is instrumented with perceived returns to science.[11] Columns 3 and 4 show the results of the same OLS and IV estimations with teacher and school dummy variables added to account for unobservable time-invariant characteristics in schools and among teachers.

Table 5: Full Specification OLS and IV Estimations with School and Teacher Fixed Effects

	(1) OLS	(2) IV	(3) OLS	(4) IV
Perceived Returns	2.037**	6.047**	3.202***	11.20***
	(0.966)	(2.791)	(0.671)	(2.218)
Constant	611.1***	615.1***	611.1***	445.2***
	(22.98)	(23.15)	(11.76)	(15.99)
N	14816	14610	14816	14610
R^2	0.401	0.400	0.603	0.598
School and teacher fixed effects	NO	NO	YES	YES

Notes: * *p<0.10;* ** *p<0.05;* *** *p<0.01.* Cluster-robust standard errors in parentheses.
A full set of controls is included in each regression as per Column 5 in Table 4.

In each specification, the coefficient on perceived returns to mathematics remains positive and statistically significant, with larger coefficients in the IV estimations compared to their OLS counterparts. The size of the coefficients increases across both the OLS and IV estimations when teacher and school dummy variables are added. The level of significance for both the OLS and IV models increases from the 5% to the 1% level once school and teacher fixed effects are controlled for.

Each specification therefore supports the hypothesis that students with a higher level of perceived returns to mathematics achieve a higher score than students who have a lower perceived returns to mathematics, *ceteris paribus.* To test which specification provides consistent estimates, a Hausman test is usually used. The standard Hausman test cannot be performed with probability weighted data[12], thus the methodology of Chmelarova (2007) and Li and Konstantopoulos (2011) was followed by running the following regression:

$$mscore_i = a_0 + \beta_1 PR_i + \beta_2 residual_i + \gamma X_i + s_j + t_k + a_i + \epsilon_i \quad (6)$$

[11] The first stage regression of perceived returns to mathematics on perceived returns to science and the other covariates is presented in Appendix Table A2. The results show a strong and significant effect of perceived returns to science on perceived return to maths as is necessary for the instrument to be valid.
[12] The Hausman test run on the unweighted sample shows that the coefficients obtained from the OLS and IV estimations are not significantly different (p-value = 0.1691).

Where $residual_i$ is the residual term obtained from the first stage of the IV estimation – the regression of perceived returns to mathematics on perceived returns to science and other observables. The other components of equation (6) have been defined as per equation (1). The result of estimating equation (6) using OLS is shown in Table 6. The statistically insignificant coefficient on the residual term (Table 6 below) indicates no significant difference between the OLS and IV estimates of the model without teacher and school fixed effects, thus, OLS estimation is preferred as it is more efficient.

Table 6: Results of Hausman Test

	(1)
residual	-4.370
	(3.040)
Constant	615.1***
	(23.67)
N	14610
R^2	0.402

Notes: * *p<0.10; *** *p<0.05; **** *p<0.01.* Cluster-robust standard errors in parentheses.
A full set of controls is included in each regression as per Column 5 in Table 4.

4.2 Testing the Sub-Hypotheses

The above analysis shows that there is strong evidence to support the main hypothesis that students who have a higher level of perceived returns to mathematics perform better than students who have a lower level of perceived returns to mathematics *ceteris paribus*. To gain a deeper understanding of how the different forms of motivation interact, the interaction between perceived returns to mathematics and intrinsic motivation for mathematics is analysed next. More specifically, I test whether students with high levels of perceived returns *and* intrinsic motivation perform better than students only exhibiting one or neither type of motivation (as per Hypothesis 2).

Table 7 displays the results of the OLS and IV estimates with and without accounting for school and teacher fixed effects in columns 1-4. In all the estimations, as found in the analysis of Hypothesis 1 above, perceived returns to mathematics is positively associated with mathematics performance. The coefficients on intrinsic motivation are also positively associated with mathematical achievement in all the specifications and statistically significant at the 1% level.

Table 7: Interactions Between Perceived Returns to Mathematics and Intrinsic Motivation

	(1) OLS	(2) IV	(3) OLS	(4) IV
Perceived Returns	2.990**	7.261**	4.065***	12.22***
	(1.234)	(3.602)	(0.796)	(2.778)
Intrinsic Motivation	7.138***	6.008***	11.17***	8.824***
	(0.833)	(1.119)	(0.655)	(0.896)
Perceived Returns*Intrinsic Motivation	1.326*	1.933	1.192**	1.641
	(0.711)	(1.825)	(0.528)	(1.541)
Constant	608.8***	611.5***	454.3***	452.7***
	(23.23)	(23.87)	(15.96)	(17.34)
N	14816	14610	14816	14610
R^2	0.401	0.401	0.604	0.599
School and teacher controls	NO	NO	YES	YES

Notes: * *p<0.10;* ** *p<0.05;* *** *p<0.01.* Cluster-robust standard errors in parentheses.
A full set of controls is included in each regression as per Column 5 in Table 4.

In support of Hypothesis 2, the interaction between perceived returns to mathematics and intrinsic motivation has a positive coefficient that is statistically significant in the OLS specifications. This indicates that there is a positive multiplicative effect of perceived returns to mathematics and intrinsic motivation for mathematics: the positive effect of having high perceived returns to mathematics is enhanced by having high intrinsic motivation for mathematics and vice versa. The level of significance of the interaction between perceived returns to mathematics and intrinsic motivation in the OLS estimations increases from the 10% level to the 5% level when teacher and school fixed effects are controlled for. In the IV estimations, the coefficients on the interaction between perceived returns and intrinsic motivation are positive and sizeable, but no longer statistically significant. However, the Hausman test with the residual of the first stage of the IV regression shows a statistically insignificant coefficient (see Appendix Table A3, Column 1), thus the OLS specification provides more efficient estimates.[13]

To gain a richer characterisation of the relationships between perceived returns, intrinsic motivation for mathematics, and student achievement in mathematics, the interactions between different levels of perceived returns to mathematics and intrinsic motivation, and their relationship with the mathematics score is shown in Graphs 2 and 3 below.

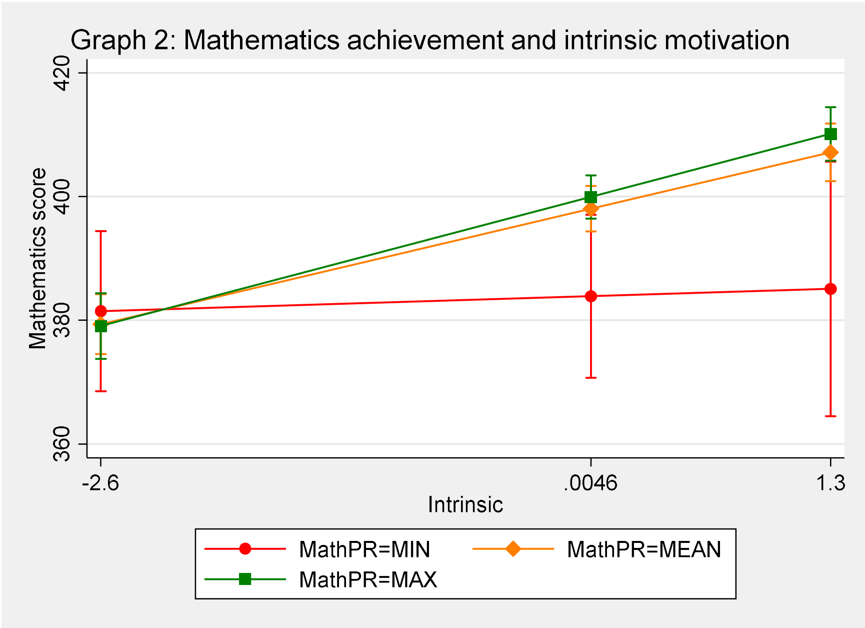
[13] The standard Hausman test on the unweighted sample shows that the difference between the coefficients of the OLS and IV estimation are not statistically significant with a p-value of 0.2256.

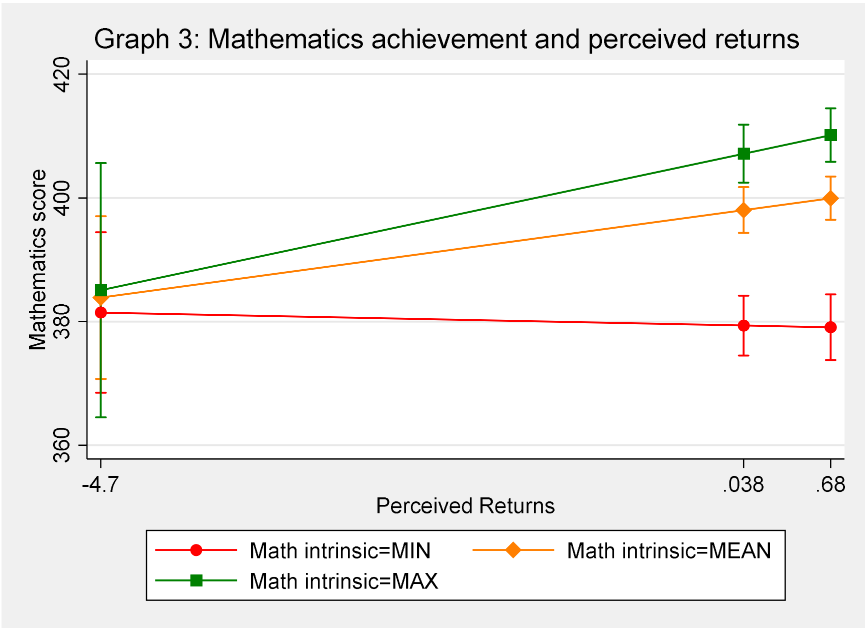
Graph 2 shows the relationship between mathematics results and intrinsic motivation at different levels of perceived returns to mathematics. The different levels of each of the constructs are defined as follows: the lowest level of the variable in question corresponds to the minimum value on the relevant scale, so for perceived returns to mathematics, the low level corresponds to a student who responded “Disagree a lot” to all of the statements used to construct the perceived returns to mathematics variable. The highest level corresponds to the maximum value on the scale (a student who responded “Agree to all” to all the statements) and the middle level corresponds to the mean level on the relevant scale.

From Graph 2 it can be seen that students who have a low level of perceived returns to mathematics and high intrinsic motivation for mathematics perform no better than students who have a low level of perceived returns to mathematics and low intrinsic motivation for mathematics (the mathematics scores lie within the same confidence interval). Students who have medium and high levels of perceived returns to mathematics perform significantly better at higher levels of intrinsic motivation.

The slope of the line showing the relationship between mathematics results and intrinsic motivation is steeper at higher levels of perceived returns to mathematics – suggesting that the positive relationship between intrinsic motivation for mathematics and mathematics achievement is enhanced by having a higher level of perceived returns to mathematics (as suggested by the positive coefficient attached to the interaction between perceived returns to mathematics and intrinsic motivation in Table 7). This being said, due to overlapping confidence intervals it cannot be said that students who have a high level of perceived returns to mathematics performs significantly different to a student who has a medium level of perceived returns at every level of intrinsic motivation.

Graph 3 shows the relationship between mathematics achievement and perceived returns to mathematics at differing levels of intrinsic motivation. Students with low levels of intrinsic motivation perform no better when levels of perceived returns to mathematics are higher, thus, perceived returns to mathematics as a form of motivation shows no correlation with higher mathematics scores when students have a low level of intrinsic motivation for mathematics. Students who have medium and high levels of intrinsic motivation perform better at higher levels of perceived returns to mathematics. Once again, the positive multiplicative effect of the interaction between perceived returns to mathematics and intrinsic motivation can be observed in the increasing gradient of student achievement and intrinsic motivation at higher levels of perceived returns to mathematics – the difference in performance at each level of intrinsic motivation becomes larger as perceived returns to mathematics increases and vice versa.





Both graphs further illustrate the information presented Table 7 above, that perceived returns to mathematics and intrinsic motivation for mathematics are both individually, as well as jointly associated with higher student achievement in mathematics. In other words, there are higher returns to having higher perceived returns to mathematics when intrinsic motivation is also high. The results presented above provide support to Hypothesis 2, as, according to the OLS estimations, a student with high perceived returns to mathematics and high intrinsic motivation for mathematics performs better than a student with only high intrinsic motivation, who in turn performs better than a student with only high perceived returns to mathematics.

From the graphs it can also be seen that the relationship between different levels of intrinsic motivation on mathematics achievement is more certain, as there is less overlap in confidence intervals (in Graph 2 for example, the mathematics score relating to the interaction between the highest and lowest level of perceived returns to mathematics and intrinsic motivation is only significantly different at the highest level of intrinsic motivation). This could perhaps be a consequence of the framing of the questions in the TIMSS questionnaire possibly not capturing the extent to which perceived returns to mathematics motivates a student.

The analyses above have shown support for the notion that non-cognitive skills are important for fostering academic achievement. As stated in Section 1, the South African literature on non-cognitive skills in education is scarce, thus, it cannot be said with certainty whether the relationships found in the international literature hold in the unique South African context with its vast inequalities in opportunity. It has been shown in the analyses above that, on average, a student who has higher perceived returns to mathematics performs better than a student with low perceived returns to mathematics *ceteris paribus.* This finding is particularly interesting in the South African context, as, incorporating information on the perceived returns to mathematics in curriculum documents could be a cost-effective way to improve mathematical achievement in such a resource-constrained country. This leads one to question whether the positive relationship between perceived returns to mathematics and mathematical achievement holds in poorly resourced schools that lack functionality. In other words, could highlighting perceived returns to mathematics somewhat bridge the gap in performance that a lack of access to school resources creates, or is the deficit of being in a poorly resourced school too large to be recovered through fostering non-cognitive skills?

To explore the answer to this question, interactions between perceived returns to mathematics and school location are presented in Table 8 (as per Hypothesis 3). The coefficients on perceived returns to mathematics are positive and statistically significant at the 1% level in both the OLS and IV specification, and the size of the coefficient on perceived returns is larger in the IV specification (recall that school and teacher fixed effects could not be included here as there would be no variation in the proxy for school resources and functionality, namely school location).

The coefficients on the school location variables are positive in both specifications and grow larger as the location becomes more urban (with rural school location being the omitted category). The school location category with the largest coefficient is the suburban category in both specifications. All school location categories except "Small town" bring significantly better returns to mathematics achievement (significant at the 1% level) as compared to a rural school location in both specifications.

Table 8: Interaction Between Perceived Returns to Mathematics and School Location

	(1) OLS	(2) IV
Math perceived returns	7.423***	14.97***
	(1.691)	(3.502)
School location: Small town	7.132	6.705
	(4.651)	(4.559)
School location: Medium city	27.21***	26.62***
	(7.563)	(7.444)
School location: Suburban	36.59***	36.06***
	(6.695)	(6.482)
School location: Urban	28.95***	28.73***
	(5.278)	(5.196)
Small town*Math perceived returns	-6.212***	-11.17***
	(2.083)	(4.170)
Medium city*Math perceived returns	-9.791***	-12.91*
	(2.660)	(7.100)
Suburban*Math perceived returns	-7.318***	-10.99*
	(2.365)	(6.433)
Urban*Math perceived returns	-10.54***	-16.43***
	(2.461)	(5.732)
Constant	613.3***	618.4***
	(22.08)	(21.62)
N	14816	14610
R^2	0.404	0.402
School and teacher controls	NO	NO

Notes: * *p<0.10; *** *p<0.05; **** *p<0.01.* Cluster-robust standard errors in parentheses.
A full set of controls is included in each regression as per Column 5 in Table 4.

The interaction terms between the school location variables and perceived returns all have negative and statistically significant (1% level) coefficients in both specifications. This implies that perceived returns to mathematics and (a more urban) school location have a moderating effect on each other. Thus, it seems that having a high level of perceived returns could potentially go some way to closing the deficit in performance that being in a less well-equipped school creates.

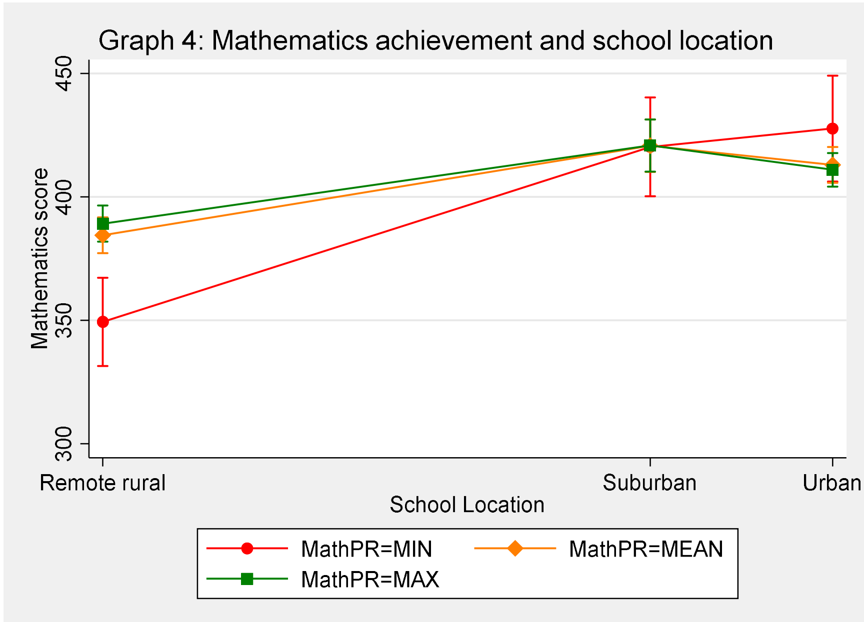
The results of the Hausman test (Appendix Table A3, Column 2) show that the results of the OLS and IV estimations are not significantly different, thus the OLS estimation is preferred as it is more efficient.[14] Also, important to note is that, although not shown here due to space constraints, the coefficients on other covariates obtain the expected results for all estimations performed above.

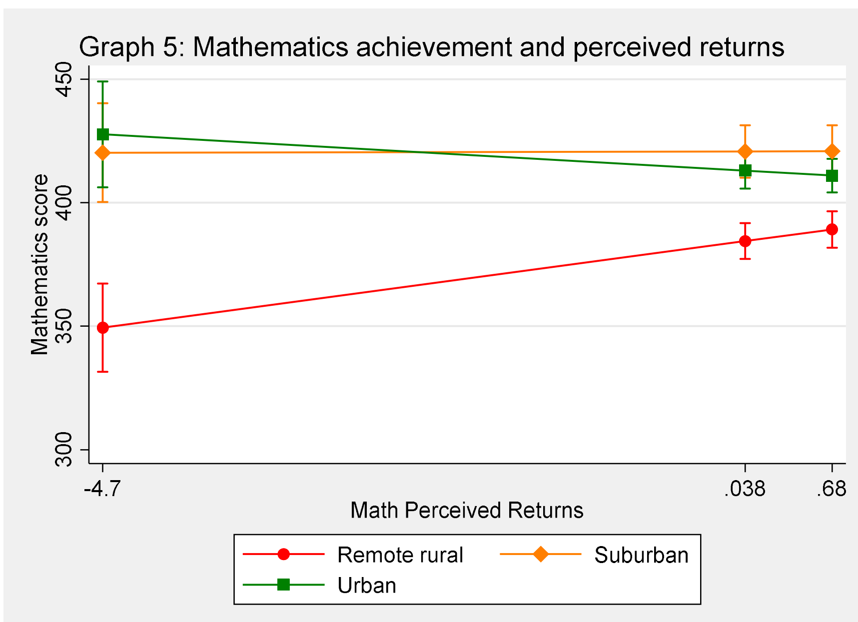
To provide a better visualisation of these results, Graphs 4 and 5 below show the relationship between mathematics achievement and school location at differing levels of perceived returns to mathematics (as defined above), and the relationship between mathematics achievement and perceived returns to mathematics at different levels of school location (ordered from less urban to more urban), respectively.

In Graph 4, a clear distinction in performance can be seen between students in a rural school with different levels of perceived returns: A student in a rural school with high perceived returns to mathematics performs better than another student in a rural school who has low perceived returns to mathematics *ceteris paribus.* It can also be seen that as student achievement converges at the suburban category, the gradient of the relationship between mathematics achievement and school location is flatter at higher levels of perceived returns to mathematics. This illustrates the result of the negative coefficient attached to the interaction between perceived returns and school location in Table 8: at higher levels of perceived returns to mathematics, the gains in performance from moving to a more urban school diminishes. The intersection in performance seen at the suburban school location is due to the suburban school location netting the highest returns to performance but being classified as the category below urban.

In Graph 5 it can be seen that being in a more urban school location grants higher returns to mathematical performance than being in a rural school at every level of perceived returns to mathematics. Again, the diminishing returns to perceived returns to mathematics in a more urban school can be observed by the flatter gradients of the lines showing the relationship between mathematics performance and perceived returns to mathematics in more urban school locations, with the level of performance of students in urban and suburban schools intersecting as perceived returns to mathematics increases.

[14] Hausman test on the unweighted sample shows that the OLS and IV estimations are only significantly different at the 10 % level (p-value = 0.0799).





Graph 5 shows that higher perceived returns to mathematics has a greater positive impact on the mathematics results of a student in a more rural school, with each increase in perceived returns resulting in a substantially higher increase in mathematics achievement than seen in students in a more urban school setting. This shows that extrinsic motivation through perceived returns to mathematics goes some way towards closing the deficit in performance that being in a less well-equipped school leaves – the difference in performance at each level of school location decreases at increasing levels of perceived returns and vice versa. It can also be seen in this graph, however, that perceived returns to mathematics is not enough to completely make up for the deficit of a lack of school resources as students in rural schools score lower than students in suburban and urban schools at every level of perceived returns.

As in the results presented in the previous section, school location is a stronger predictor of mathematical achievement than perceived returns to mathematics, as less overlap in confidence intervals can be seen in Graph 5 as compared to Graph 4.

Thus, the above analysis shows that perceived returns matter (and even more so for a student in a poorer school setting), but being in a better equipped school matters more for mathematics achievement: a student in a rural school with high perceived returns to mathematics will perform better than a student in a rural school with low perceived returns to mathematics *ceteris paribus*, but a student in a rural school with high perceived returns to mathematics will still perform worse than a student in an urban school with low perceived returns to mathematics *ceteris paribus.* Rather poignantly, the major finding is that higher perceived returns to mathematics are important, but it is not a quick fix for the dysfunctional education system in South Africa.

5. Conclusion

The objective of this study was to further the research on non-cognitive skills and their association with academic achievement in the South African context. Specifically, the aim of this study was to investigate the relationship between students' perceived returns to mathematics and its relationship with mathematics achievement. The study was conducted using the TIMSS South Africa 2019 dataset for the grade 9 student cohort, and both instrumental variable analysis and fixed effects were used to try and account for endogeneity and unobserved heterogeneity as best as possible. As was predicted, the results of the analyses found that students with higher levels of perceived returns to mathematics perform better than students with lower levels of perceived returns to mathematics, *ceteris paribus,* and this result was robust across the methods used.

To gain a deeper understanding of the effect of perceived returns to mathematics, the interactions between perceived returns to mathematics and intrinsic motivation, and perceived returns to mathematics and school location were also investigated. The main questions of interest regarding these interactions were: (1) Given that a student has low intrinsic motivation for mathematics, is there a way to extrinsically motivate them through the means of perceived returns to mathematics? and (2) can perceived returns to mathematics help mitigate the disadvantages students face in less-resourced, less-functional schools in South Africa?

The results of the analyses of the interactions between perceived returns to mathematics and intrinsic motivation show that there is a positive multiplicative effect of perceived returns and intrinsic motivation on mathematics achievement: the gap in performance between students with high intrinsic motivation grows as levels of perceived returns to mathematics increases and vice versa. Thus, the positive effects of high intrinsic motivation on mathematics achievement are enhanced by having high perceived returns to mathematics as well. The analyses also showed that students who have a low level of intrinsic motivation but have a high level of perceived returns do not perform significantly differently from students who have both a low level of intrinsic motivation and perceived returns. In other words, perceived returns to mathematics do not significantly affect mathematics achievement when a student has a low level of intrinsic motivation for mathematics.

The estimations of the interactions between perceived returns to mathematics and school location show that these variables have a moderating effect on one another – the positive effect that being in a more urban school has on mathematics achievement diminishes as perceived returns to mathematics increases. Thus, the deficit in performance that being in a more rural school creates can be somewhat recuperated through the means of increased perceived returns to mathematics. This shows that perceived returns matter for mathematics achievement, and even more so in the challenging circumstances of the rural school context.

An important finding of this analysis, however, is that, even though perceived returns to mathematics matters more in a rural school than in an urban school, a student in a rural school with high perceived returns to mathematics will still perform worse than a student in an urban school with low perceived returns to mathematics *ceteris paribus.* This shows that perceived returns to mathematics alone cannot solve the structural issues of inequality in schooling that apartheid policies have left in their wake, and that much more needs to be done to improve the functionality of poorer schools and create the opportunity for individuals from previously disenfranchised backgrounds to obtain quality education.

Further, while it is encouraging that the coefficients attached to the perceived returns variables remain significant across all the specifications, the size of these coefficients is comparatively small, with a one standard deviation increase in perceived returns to mathematics translating into an improvement in scores of between two to twelve points on the TIMSS mathematics assessment. This is a similar change in scores as seen from a one standard deviation increase in teacher accountability, home SES and bullying (with the relationship running in the opposite direction in this case). This pales in comparison to the increase in scores related to being in a more urban school location and learning in one's home language. This further shows key policy areas that need to be addressed to reduce the inequalities in education that apartheid has left in its wake.

Finally, it is useful to reflect on two of the key limitations of the study outlined earlier. First, extrinsic motivation, proxied by perceived returns to mathematics, is likely endogenous to performance. In other words, extrinsic motivation may be correlated with other unobserved student characteristics that themselves affect mathematics achievement, and doing better at mathematics may itself positively affect perceived returns. While the results were robust to IV analysis, I was unable to account for student-level unobserved heterogeneity fully given the nature of the cross-sectional data used.

Second, it is also important to recognise that non-cognitive skills can be more nebulous in nature and harder to measure than cognitive skills. Extrinsic motivation was proxied for by perceived returns to mathematics based on the series of statements included in the TIMSS questionnaire that students could agree or disagree with. However, the statements upon which the latent construct is based are statements which the student population generally agree with – most students generally agree that mathematics has some future value in the realm of studies, work and general life. Because the measure used in this study likely does not fully capture how strongly students are extrinsically motivated (in other words, there is likely less variation among students in perceived returns than is probably the case), estimates of the effect of perceived returns to mathematics on student achievement in mathematics may be underestimated.

Given that more advanced techniques to measure non-cognitive skills are often prohibitively expensive, it may be more prudent to find ways to improve the questions included in the TIMSS questionnaire, especially seeing as the data are collected frequently and are utilised across a range of countries in the field of education research. One solution to this issue may be to ask students to rank the presented response options in order of what motivates them *most* to put forth the effort to study mathematics, with options ranging across the motivation autonomy spectrum. This will provide researchers with an indication of where the student lies on the spectrum of motivation (for example, whether a student is more intrinsically or extrinsically motivated) and allow for more accurate analyses of the effect that different types of motivation have on academic achievement. An example of such a set of questions, with further description of the logic to this form of questioning, is included in Appendix A4.

Overall, and despite these limitations, the study was able to contribute to the scarce South African research on the role of non-cognitive skills in academic achievement. The findings suggest that, indeed, extrinsic motivation matters for mathematics achievement, its effect is compounded when a student is also intrinsically motivated, and it matters more for children in more rural (less well-resourced) schools. The study also provides further impetus to improve the way non-cognitive skills are captured in large-scale international education quality assessments, with better framing and structuring of the questions being one useful option.

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Appendix

Table A1: The Relationship Between Perceived Returns and Mathematics Performance Using Plausible Values Regression Analysis

	(1)	(2)	(3)	(4)	(5)
Math perceived returns	10.68***		7.183***	3.113***	2.193**
	(1.371)		(1.158)	(1.108)	(1.040)
Math intrinsic		5.173***	7.700***	7.968***	8.090***
		(1.312)	(1.207)	(1.192)	(1.174)
School location: Small town			13.90**	9.136*	7.152
			(6.122)	(5.535)	(5.208)
School location: Medium city			47.32***	33.80***	27.58***
			(9.972)	(8.288)	(7.354)
School location: Suburban			57.68***	44.03***	36.55***
			(8.899)	(8.118)	(7.150)
School location: Urban			48.65***	34.94***	28.98***
			(6.569)	(5.863)	(4.969)
Student feels safe at school: Disagree a little			25.30***	22.57***	18.33***
			(4.247)	(4.176)	(3.952)
Student feels safe at school: Agree a little			21.29***	20.59***	18.43***
			(4.211)	(3.915)	(3.592)
Student feels safe at school: Agree a lot			11.51***	10.89***	11.57***
			(4.071)	(3.694)	(3.414)
Bullying scale			-15.97***	-14.71***	-11.91***
			(0.990)	(0.957)	(0.998)
Math class size			-0.774***	-0.562***	-0.460***
			(0.153)	(0.132)	(0.124)
Teacher accountability			12.18***	9.952***	8.847***
			(2.201)	(1.974)	(1.730)
Parents think math is important: Disagree a little				28.73***	26.73***
				(6.002)	(5.764)
Parents think math is important: Agree a little				31.91***	30.57***
				(4.995)	(5.075)
Parents think math is important: Agree a lot				46.58***	40.50***
				(5.009)	(5.064)
Books in home: 11-25				-1.587	-3.231*
				(1.831)	(1.743)
Books in home: 26-100				19.14***	12.95***
				(2.724)	(2.319)

Books in home: 101-200				34.59***	28.98***
				(5.576)	(4.985)
Books in home: >200				31.70***	26.51***
				(6.750)	(6.177)
Home SES				14.327***	10.241***
				(0.936)	(0.817)
Speaks test language at home: Sometimes					7.320**
					(3.591)
Speaks test language at home: Almost always					32.83***
					(4.419)
Speaks test language at home: Always					41.58***
					(4.974)
Female student					-5.755***
					(1.635)
Student age					-17.19***
					(1.294)
Constant	397.6***	397.7***	395.1***	347.7***	606.4***
	(2.443)	(2.519)	(9.859)	(10.19)	(26.50)
N	14816	14816	14816	14816	14816
R^2	0.018	0.004	0.266	0.334	0.410
School/classroom level factors	NO	NO	YES	YES	YES
Home level factors	NO	NO	NO	YES	YES
Other student-level factors	NO	NO	NO	NO	YES

Notes: * *p<0.10;* ** *p<0.05;* *** *p<0.01.* Cluster-robust standard errors in parentheses.

Table A2: First Stage Regression of 2sls IV Estimation

Dependant variable= Perceived returns to mathematics	(1)
Perceived returns to science	0.282***
	(0.0116)
Constant	-0.992***
	(0.250)
N	14610
R^2	0.394

Notes: * *p<0.10;* ** *p<0.05;* *** *p<0.01.* Cluster-robust standard errors in parentheses.

A full set of controls was included in the regression, although not shown here. The only covariates with a higher coefficient than perceived returns to science were the parental involvement variables (not shown here) proxied by student agreement with the statement “My parents think mathematics is important”. This provides further support for the sentiment that perceived returns can be shaped by external environments.

Table A3: Hausman tests for OLS vs IV Estimates

	(1)	(2)
residual	-4.040	-4.923
	(2.667)	(3.023)
Constant	611.9***	617.8***
	(24.00)	(22.57)
N	14610	14610
R^2	0.403	0.405

Notes: * *p<0.10;* ** *p<0.05;* *** *p<0.01.* Cluster-robust standard errors in parentheses.
A full set of controls is included in each regression as per Column 5 in Table 3.

Table A3 shows the Hausman test with the residual of the first stage of the IV regressions. Column 1 shows the results of the test relating the Hypothesis 2 (the interaction between perceived returns to mathematics and intrinsic motivation) and column 2 shows the results of the test relating to Hypothesis 3 (the interaction between perceived returns to mathematics and school location).

A4: Respecification of Questions to Better Capture Student Motivation

In Section 3, I put forth that the formulation of the questions in the TIMSS student questionnaire with regards to the variables used to construct the perceived returns scale may produce underestimated results of the effect that perceived returns has on mathematics, as these are statements that most students generally agree with and so may not necessarily capture the extent to which perceived returns to mathematics actually motivates the student. This, in turn, makes it difficult to place students on the spectrum of motivation proposed by Ryan and Deci (2000) in the literature review above, and truly measure the relationship between different types of motivation and mathematics performance.

A suggestion to address this issue is to ask students to rank what motivates them to study mathematics from highest to lowest and provide response options that cover the full range of the motivation spectrum, as presented in the exhibit below. Thus, from student responses to this question, it becomes clear what the main source of motivation for the student is (and what type). This way more nuanced analyses of the relationship between different types of motivation and mathematics achievement is possible.

Exhibit A4: Proposed Alternate to TIMSS Question Framing

Rank these options in the order of what most motivates you to put forth the effort to study mathematics with column 1 being the most motivating factor and column 4 being the least:

Fill one circle for each line and column.

	Most motivating 1	2	3	**Least motivating** 4
a) Mathematics is a compulsory subject	O	O	O	O
b) I generally want to do well academically	O	O	O	O
c) Mathematics is valuable for my future career prospects	O	O	O	O
d) I find mathematics interesting	O	O	O	O

The options in the above exhibit present the spectrum of motivation, ranging from externally regulated, extrinsic motivation in option a, to introjected regulation (extrinsic motivation) in option b, internally regulated extrinsic motivation for option c (this would be the category in which perceived returns to mathematics falls), and intrinsic motivation in option d. More options can be added or the options can be made more general (but still capture the different types of motivation), this exhibit is mainly for illustrative purposes.