Long Term Effects of Free Primary Education on Educational Achievement: Evidence from Lesotho*

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Abstract

Many Sub-Saharan African countries instituted fee-elimination policies, and this led to a significant increase in school enrolment and a learning crisis. However, it is unclear whether fee-elimination policies have contributed to the decline in the quality of education and whether these learning effects are long-lasting. I, therefore, estimate the long-term effects of the free primary education programme on educational achievement in Lesotho. The programme was phased-in grade-by-grade, beginning with grade one in 2000. This implementation strategy created changes in programme coverage across age (and grade) groups over time. I employ a semiparametric difference-in-differences strategy that exploits these variations to identify the long-term effects of the programme, using university administrative data for student cohorts with and without free primary education. The results indicate that the effect of free primary education on academic performance is bounded between 0 and 2.9 percent, implying that the programme increased enrolment without hurting education quality.

JEL Classification: H52, I22, I28, 015

Keywords: Free Primary Education, Educational achievement, Long-term effects, Lesotho

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1 Introduction

The Dakar Framework for Action (DFA), adopted by World Education Forum in 2000, called for complete, free, and compulsory quality education, with the aim to redress global educational inequalities (UNESCO, 2000, p.8). Since then, several sub-Saharan African countries have instituted free primary education (FPE) programmes[1] by abolishing all primary school user fees. Several studies have quantified the short-term effects of the FPE programmes in sub-Saharan Africa on school enrolment, drop-out, and grade progression (see Deininger 2003; Al-Samarrai and Zaman 2007; Nishimura *et al.* 2008; Grogan 2009; Lucas and Mbiti 2012; Hoogeveen and Rossi 2013; Moshoeshoe *et al.* 2019). These studies find that FPE increased enrolment, reduced school drop-out, and reduced grade-progression. Therefore, largely owing to FPE programmes, the primary school enrolment rate in the developing world has reached 91 percent (UNDP, 2016), with 94 percent and 74 percent of children worldwide completing primary education and lower secondary education, respectively (World Bank, 2016, 2018).

However, school attendance is different from learning. The main problem now is that millions of children finish primary school without acquiring functional literacy and numeracy skills, and this is more pronounced in sub-Saharan Africa (World Bank, 2018; Filmer *et al.*, 2020). Therefore, achieving inclusive and equitable quality education by 2030 is the fourth most important Sustainable Development Goal (SDG) under the 2030 Agenda.

Since the Millennium Development Goals, the SDGs' predecessor, focused mainly on increasing access to schooling, it is generally believed that the current learning crisis is partly due to school fees' elimination programmes. However, a few studies that quantify the short-term effects of these FPE programmes, and similar fee elimination policies in Africa, on education quality (i.e. test scores) find mixed evidence. Lucas and Mbiti (2012), for example, apply a difference-in-differences (DID) strategy, exploiting the variation in pre-programme primary school drop-out rates across districts in Kenya to estimate the effect of FPE on primary school completion rate and test scores. They find marginal negative effects of FPE on test scores, but large and positive effects on primary school completion rate. Blimpo *et al.* (2016), on the other hand, find positive effects of the Gambian Girls' Scholarship programme (a secondary school fee elimination programme for girls) on student access and learning, using a DID strategy. In as much as this question remains open, data availability remains a hinderance in answering it, and this paper does not attempt to address it for the same reasons.

All else held constant, the negative (or positive) effects of FPE on learning may still show up later on in a child's academic life. According to Cunha *et al.* (2006), achievement test scores are determined by skills or abilities (both cognitive and noncognitive)[2] that are malleable to environ-

[1] Including but not limited to Burundi, Cameroon, Eswatini, Ghana, Kenya, Lesotho, Mozambique, Namibia, Rwanda, Tanzania, and Zambia.

[2] Cognitive skills are malleable to environmental factors up to age 10 or so, while noncognitive skills are malleable for a much longer time (Cunha *et al.*, 2006)

mental (e.g. family and school) influences. These skills are self-productive and complementary. That is, skills acquired at primary school may augment skills attained at the secondary and university levels, and that skills acquired at primary school may raise the productivity of education investments at the secondary and university levels.

Therefore, it is reasonable to assume that FPE, through its influence on school inputs and environments, will have lasting effects of education quality. However, this hypothesis has not yet been tested.

If we are to build a productive, talented, and diverse labour force, it is essential to know well in time the effects of the implemented policies so that they can either be scaled up (if the effects are positive) and/or changed (if the effects are negative). Therefore, this paper estimates the long-term effects of FPE on education performance.

Apart from the fact that this paper is among the first studies to estimate the long-term effects of FPE policies in sub-Saharan Africa, it contributes to several strands of literature. First, it contributes to the literature that looks at the long-term impacts of schooling inputs on educational outcomes. For example, Fredriksson *et al.* (2013) look at the long-term effects of class size on human capital development. They find that smaller class sizes improve cognitive and noncognitive ablilities at age 13, and improve achievement test scores at age 16. Second, it adds to the literature that looks at the short- term impacts of fee eliminations on educational outcomes in developing countries (Grogan, 2009; Lucas and Mbiti, 2012; Hoogeveen and Rossi, 2013; Chyi and Zhou, 2014; Blimpo *et al.*, 2016; Moshoeshoe *et al.*, 2019). Lastly, it adds to the small, but growing, literature on the long-term effects of schooling subsidy programmes (including tuition fee eliminations) on human capital development. For example, Xiao *et al.* (2017) estimate the long-term effects a free compulsory education reform in rural China on educational attainment, cognitive skills and health. They find that the reform had long lasting positive effects on educational attainment and cognitive achievement.

I estimate the long term effects of FPE on education quality in Lesotho mainly for the following two reasons. First, unlike in many sub-Saharan African countries, the FPE programme in Lesotho was phased-in grade by grade, starting with grade one in 2000, until it covered the entire primary schooling system in 2006. This implementation strategy makes it possible to follow two cohorts of children (the FPE treated and the FPE untreated cohorts) from primary school through university level, and hence account for the underlying trends in achievement test scores of the cohorts through a difference-in-differences estimation strategy. Second, Lesotho has only one big (and premier) public university, the National University of Lesotho (NUL), and two smaller (and new) private universities, which only opened in 2007 and 2016, respectively. Therefore, it is possible to get data for a sizeable proportion of the FPE treated and untreated cohorts that have written similar standardised achievement tests.

The results indicate that the FPE programme has lasting positive effects on educational quality:

it increased university students' academic performance by between 0.42 and 1.73 percentage points (or 0.7 and 2.9 percent). The robustness checks results indicate that the increase in educational quality cannot be attributed to some positive time trend, and that these effects are stronger when the sample is narrowed to 18-22 years old, the age range appropriate for the undergraduate level. The results are also robust to model specification errors.

The reminder of the paper proceeds as follows. Section 2 presents the institutional context and policy background. Section 3 briefly provides the theoretical framework while Section 4 discusses the data and presents some descriptive statistics. In Section 5, I explain the identification strategy, and present the main results in Section 6. Section 7 concludes the paper.

2 The institutional context and policy background

2.1 The institutional context

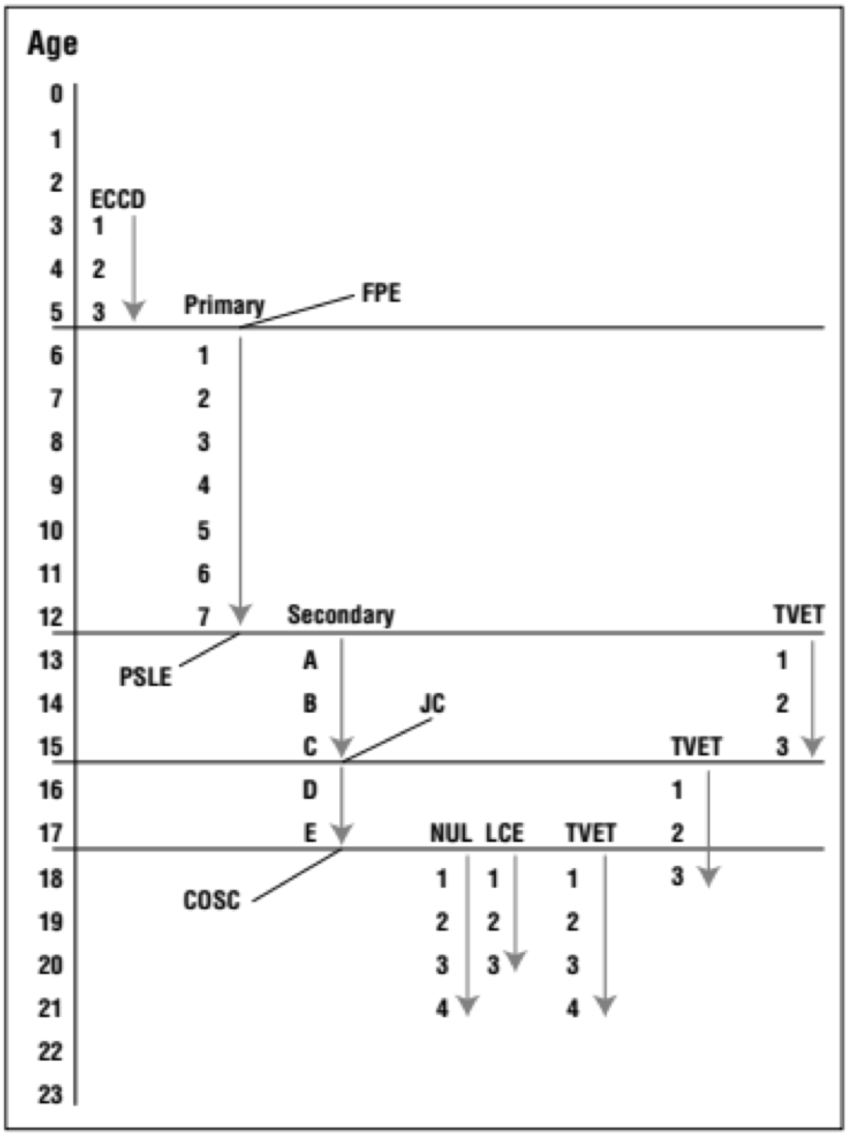
Lesotho education follows a 7-3-2-4 system, with seven years of primary education, three years of junior secondary education, two years of senior secondary education, and four years of university education (see Figure 1). The official age of entry into primary schooling is six years, such that by age twelve, children should be in grade seven. This implies that the official primary school-age is 6 to 12 years old, and that for secondary education is 13 to 17 years old.

At the end of primary school, students take the national exit exam, the Primary School leaving Exam (PSLE), in order to enter the lower (junior) secondary school. After 3 years of junior secondary education, students take the Junior Certificate (JC) exam to progress to senior secondary, at the end of which they take the Cambridge Overseas School Certificate Exam (COSC).[3] Students can also enrol in different Technical and Vocational Education and Training (TVET) after taking either the PSLE, JC, and/or COSC exams. Given that secondary education is not free in Lesotho, enrolment into TVET is largely dictated by a child's academic performance (low performance) and/or household wealth.

Unlike many other countries, most primary schools in Lesotho (about 85 percent) are owned and controlled by different churches (see Moshoeshoe *et al.*, 2019), and these churches are represented in the national education advisory board by their appointed education secretaries (Ambrose, 2007). Non-religious private schools constitute about one percent of primary schools, and are not covered by the FPE policy. The picture is very much similar even at the secondary or high school level because most church-owned primary schools have their secondary schools nearby. However, the share of non-religious private secondary schools is slightly higher than that at primary level. As of 2014, there were about 1.4 percent non-church private high schools (Bureau of Statistics, 2015), and these are concentrated in four districts of the country, namely, Berea, Botha-Bothe, Leribe

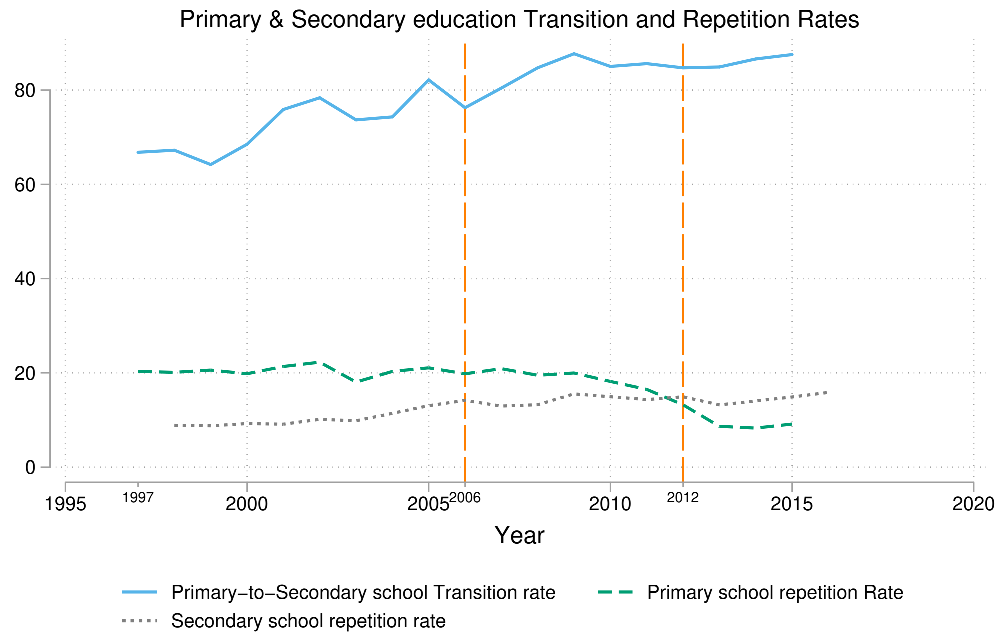
[3] This is now called Lesotho General Certificate of Secondary Education (LGCSE). Through out this paper, COSC and LGCSE are used interchangeably.

Figure 1: Education System in Lesotho



Source: (Liang *et al.*, 2005, p.25). *Notes*: ECCD refers to Early Childhood Care and Development; LCE refers to Lesotho College of Education; and TVET refers to Technical and Vocational Education and Training.

Figure 2: Primary-to-Secondary education Transition rate, and Repetition rates, 1997-2016



Source: Own representation using data from UN Institute of Statistics.

and Maseru. Notwithstanding this co-ownership structure, and except for non-church private schools, all schools follow the same national curriculum provided by the Ministry of Education and Training (MOET). Further, the government has an overall authority in pronouncing education policies, management and regulation of education, training of teachers, and teachers' placements, and deployments within government and church-owned schools. But some church-owned schools do at times privately hire contract teachers at their own costs.

With regard to students' progression within the system, the *de jure* government policy since 1967 is that of automatic grade promotion at primary school level but, *de facto*, schools still practice grade retention (Ambrose, 2007).[4] Figure 2 indicates that, between 2000 and 2015, primary school repetition rate was about 20 percent until 2010, after which it dropped to about 14 percent in 2015. During this period, the primary education repetition rate averaged about 17.3 percent and the PSLE exam failure rate fluctuated between 12 percent and 17 percent. Thus, coupled with delayed school enrolment, the high grade retention rate implies that in any given year (or grade) there are children of different cohorts Moshoeshoe *et al.* (2019).

There is grade retention policy at secondary school level. Figure 2 further shows that, while the transition rate between primary and secondary education is high (about 81 percent), the repetition rate in secondary education is also high, averaging about 12.6 percent between 2000 and

[4]However, since 2010, there has been an increased push for automatic grade promotion at the primary school level. But this latest policy call does not affect the cohorts which this paper studies (i.e. those that were in primary school during the years 2000 to 2006).

2015. Further, the JC exams failure rate is high; it fluctuated between 24 percent (recorded in 2004) and 32 percent (recorded in 2009 when the first FPE students wrote JC exams) (Bureau of Statistics, 2015). This high failure rate could explain the high dropout rate, of 16 percent at secondary school level. Therefore, those who ultimately get into university are a select group of motivated and high ability students who potentially come from high income households.

Beyond physical and monetary costs, there are no regulatory restrictions on school choice in Lesotho. Thus, school choice is largely determined by school availability, school's past pass rates, parental wealth, and parental tastes for education. High performing high schools generally attract students from across the country, and have stricter entry requirements. Hence, to cope with the high demand, such high schools normally administer entry exams, and often do not re-admit their students whose JC exam's performance is considered poor (usually second class pass and below). This implies that different schools largely cater for different types of students with regard to performance.

As of 2013, there were about 13 higher education institutions, 8 (i.e. 62 percent) of which are public institutions. The National University of Lesotho (NUL) is the main tertiary institution in Lesotho, and remained the only local bachelor's and master's degree-awarding institution until 2007. The university admits about 44 percent[5] and 89 percent of Lesotho's undergraduate and postgraduate students' population, respectively (Council on Higher Education, 2013).

2.2 Policy background

Lesotho instituted the FPE programme in 2000 in order to meet the Millennium Development Goal (MDG) of ensuring that primary education is free and available to all (UNESCO, 2000). As mentioned earlier, Lesotho's implementation strategy was different from that followed by other African countries. School fees were eliminated sequentially on a grade-by-grade basis starting with grade one in 2000 such that by 2006, all seven primary school grades were under FPE. The main reason for this implementation strategy was to cushion FPE's financial impact on the public budget (Urwick, 2011).

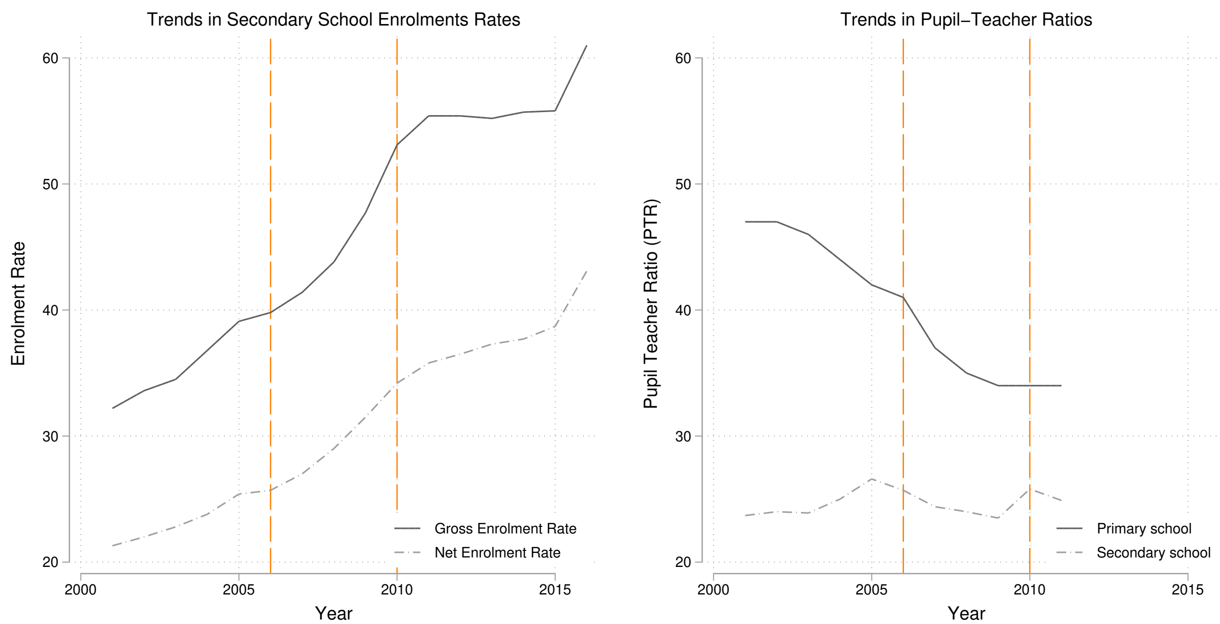
The FPE policy is an amalgamation of several programme components that address both demand- and supply-side constraints to schooling. On the demand-side, the policy involves elimination of some private schooling costs such as school fees, stationery and textbooks' costs. On the supply-side, the government recruited more teachers[6], built additional classrooms in existing schools, and new government schools where none existed before. For example, between 2002 and 2011, the number of primary schools in Lesotho increased by about 10 percent, and the primary school pupil-teacher ratio dropped from 48 to 34 pupils per teacher (MOET, 2011). This increase

[5] This is as a percent of all those enrolled in local colleges and foreign universities, mainly in South Africa.

[6] More young and qualified teachers were recruited. Between 2000 and 2007, the proportion of teachers with tertiary qualifications increase from 6 percent to 14 percent, but teacher quality, as measured by teacher performance on SACMEQ reading test, declined (see Moshoeshoe, 2015).

in infrastructure also helped to reduce the average distance to schools, and hence transportation costs. In addition to school infrastructure, the government provides annual capitation grants, furniture and teaching materials to all schools, including church/private schools (Jopo *et al.*, 2011; Lekhetho, 2013). Except for the differences in years of exposure, the supply-side programme components benefited everyone at school while fee eliminations and free stationery and textbooks exclusively benefited those covered by FPE.

Figure 3: Changes in Pupil-Teacher Ratio and Enrolment



Source: Own representation using data from various Education Statistics Reports (MOET, 2010, 2011, 2016).

Figure 3 shows changes in secondary school enrolment (demand for education), on the left panel, and pupil-teacher ratio (supply of education), on the right panel, since the introduction FPE programme. From the left panel of the figure, we can see that, while the secondary school gross enrolment rate was on the increase between 2001 and 2011, the increase was much faster between 2006 and 2010. The figure further shows that, while net enrolment rate increased through out the period, gross enrolment rate plateaued between 2011 and 2015, and then began the upward trend. The year 2007 is when the first cohort of FPE children entered secondary school level. Moshoeshoe *et al.* (2019) find that, within the first three years of the FPE policy implementation, enrolment of primary school-aged children increased by about 29 percent. Therefore, the increase in secondary school enrolment between 2007 and 2011 is partly due to the increased demand for education from the first three FPE cohorts. This first FPE cohort, which potentially had many over aged children, completed secondary education in 2011. And this partly explains the plateauing of gross enrolment rate, and the continued increase in net enrolment, between 2011 and 2015.

According to MOET (2011), the government increased the number of secondary schools and recruited more teachers in anticipation of the increased demand. This is evident in the right panel of Figure 3 that shows that secondary schools' student teacher ratio was on the increase until 2005, and then began to decline to about 1 teacher per 24 students in 2009. It is clear from this analysis, therefore, that Lesotho's FPE programme had multiple components targeted at primary schools, and it also had a knock-on effect on school resources at the secondary school level. This paper examines the long-term effects of this policy package, not its individual elements.

3 Conceptual Framework

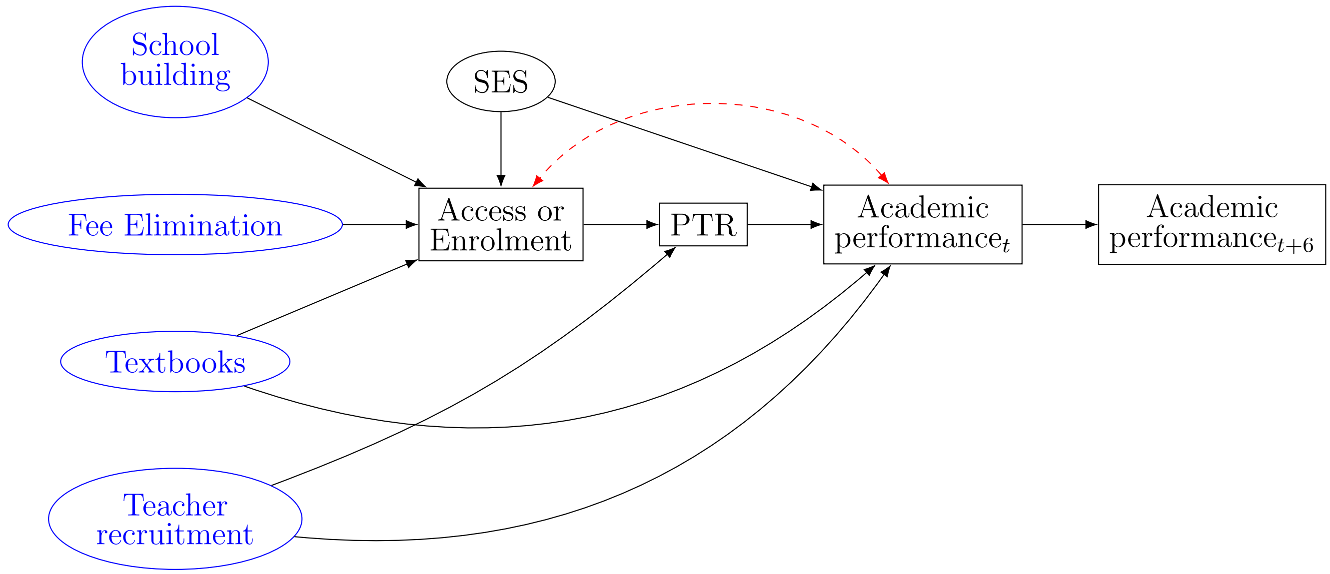
Understanding the process of a child's cognitive development has remained the preoccupation of economists since the early works of Leibowitz (1974) and Becker and Tomes (1986). According to Haveman and Wolfe (1995), a child's development is principally determined by three factors, namely: government choices regarding the amount of resources invested in education; parental investment decisions in the form of quantity and quality of resources devoted; and the child's own choices (but only past age 13 or 15). In this setting, the government moves first by making direct investment in the child and setting the economic environment, within which parents, and then children, operate. Here the view is that investment in children cannot happen outside government involvement and that this investment takes place only after the child is born.

However, Cunha, Heckman, Lochner and Masterov (2006) argue that skill (or ability) formation is a life cycle process that starts much earlier in life, from the womb, and that abilities, cognitive and non-cognitive, are malleable to environmental influences. They postulate that early and late investments in child's development are complementary. Thus, early high quality child investments increase the productivity of later child investments (i.e. skill begets skill), and this effectively places parents as very important first movers under the Haveman-Wolfe sequential framework. But equally important is the role played by the society or government in the second stage of human capital development (after birth) because early investments are only productive if there is follow-up investment.

Indeed Behrman (2010) propounds that, for children aged 6 or 7 to 15, educational achievement is partly determined by formal schooling and its characteristics, including out-of-school experiences such as homework conditional on preschool investments, individual, family, market and institutional characteristics. Hence, early quality childhood investment, both at home and at school, manifests itself in the form of high achievement and low grade retention. It is clear that achievement is a function of not only abilities but also school inputs, thereby placing family and government at the centre of the child's development.

Figure 4 is the directed acyclic graph (DAG) of the causal path ways from FPE programme components (i.e. fee eliminations, textbooks, teacher-recruitment, and school building) to academic

Figure 4: The Directed Acyclic Graph (DAG) of causal effect of FPE on academic performance



Source: Own representation. *Notes*: PTR is the Pupil Teacher Ratio; SES is socioeconomic status. The direction of the arrow (A $\rightarrow$ B) indicates the direction of the cause from node A to node B.

achievement. We can see from this figure that, because elimination of schools fees, building of more schools, and provision of textbooks reduce the costs of schooling, they are expected to affect access to schooling positively. The increase in enrolment will lead to an increase in pupil teacher ratio (PTR), all else held constant, and this will in turn affect (current or primary school) academic achievement. Recruiting more teachers will reduce PTR and, hence, improve academic achievement.

Further, textbooks availability and teacher recruitment have a direct influence on academic achievement, and students' socioeconomic status (SES) affect academic achievement directly and through its influence on access and PTR, holding all else constant. There is a positive relationship between SES and achievement. Therefore, fee eliminations will lead to an influx of low SES children into the schooling system and lower achievement. Lastly, (current or primary) academic achievement can also influence current enrolment and academic achievement in the next period, say six years later.

I therefore model knowledge acquisition as a cumulative process that combines a full history of family, community and school inputs with the child's innate ability to produce child's achievement as measured by test scores at a point in time (Todd and Wolpin, 2003). Let A_{it} be student i's academic achievement (or test scores), and $\mathbf{S}_{it}$ and $\mathbf{X}_{it}$ denote vectors of school-supplied inputs (e.g. student i's class size, school infrastructure, quality of teachers, etc) and family-supplied inputs at time t, respectively. Allowing for the idiosyncratic error, which includes all omitted inputs (observed and unobserved) and measurement error, ε_{it}, and inherited ability, a_{i0}, the general achievement production function is given as:

$$A_{it} = f(\mathbf{X}_{it}, \mathbf{X}_{it-1}, \ldots \mathbf{X}_{i0}, \mathbf{S}_{it}, \mathbf{S}_{it-1}, \ldots, \mathbf{S}_{i0}, a_{i0}, \varepsilon_{it}) \tag{1}$$

In this framework, a student's performance at the university level is influenced not only by her current individual and household characteristics, but also by current and previous school/university-supplied inputs. Because skill begets skill, the influence of past school-supplied inputs is partly reflected in the child's performance in JC and COSC/LGCSE examinations.

4 Data and Descriptive Statistics

This paper uses the National University of Lesotho's students' administrative records data for years 2010 up to 2014. It makes use of first-year and second-year students' data. As the largest and oldest undergraduate degree-awarding university in Lesotho, the NUL admits the largest share of all students who achieve the minimum score for university entry in the senior high school exit examinations. It therefore admits the largest proportion of students who have gone through the FPE system. Given that the first cohort that has gone through the FPE programme first entered university level in 2012, the second-year students are a control group, while the first years are a treatment group. I discuss this group categorisation in detail in Section 5.

The data contains information on each student's gender, date of birth, academic year, the senior high school exit (or Cambridge Overseas School Certificate (COSC)) examination pass grade, the NUL Admission Point System (APS) score[7] for each student, the high school attended, faculty, department or program of study, the overall weighted mean or year mean performance, and whether a student is local or international. The overall weighted mean (OWM) is the main outcome variable. It is calculated as the weighted sum of the final scores of core, pre-requisite, and/or elective subject courses that make a maximum of 36 credit hours, where the weights are each course's credit hours divided by 36.[8] I construct the student's district information based on the location of the high school attended[9].

Table 1 gives the summary statistics for the sample, first and second year students not exposed to FPE, 2010 to 2011, and those exposed to FPE, 2012 to 2014. There are 6,613 students who are in the first and second years of their undergraduate studies (diploma and degree programmes)

[7]APS score (commonly known as the aggregate score) is the sum of grade points/ranks for 6 COSC subjects, including English language. For example, grade A* (or A$^+$) is given point/rank 1, grade A is equivalent to 2 points, grade B is equivalent to 3 points, etc. Therefore, the lower the APS score the higher the performance in COSC exams. The lowest achievable APS score is 6 and indicates the highest level of performance in all six subjects.

[8]Suppose that a student has registered for 12 courses, each with 3 credit hours (or contact hours per week). These courses make a total of 36 credit hours, and will all be used in the calculation of the OWM. If the student scores 60% in each course, then her OWM is the weighted sum of all the 60s, where the weights are $\frac{3}{36} = \frac{1}{12}$, which equals 60%. If the student has taken courses with more than 36 credit hours, then only courses making at least 36 credit hours, starting with core and pre-requisite (i.e. required) courses, are included in the OWM calculation.

[9]Even though some students attend schools outside their home districts, a large proportion of them do attend schools within their home districts.

Table 1: Summary Statistics

Variable	Pre-FPE (2010-2011) N	Mean	Std.Dev	Post-FPE (2012-2014) N	mean	Std.Dev	$p-$value for diff.
OWM	5654	59.88	9.605	7795	59.25	9.094	0.0001
Standardized OWM	5654	0.0268	1.034	7795	-0.0204	0.970	0.0068
Female	5776	0.563	0.496	8016	0.601	0.490	0.0000
Age	5764	21.10	3.915	8004	20.89	3.588	0.0016
COSC pass							
First class	4765	0.300	0.458	7713	0.314	0.464	0.0991
Second class	4765	0.551	0.497	7713	0.571	0.495	0.0245
Third class	4765	0.149	0.356	7713	0.115	0.319	0.0000
APS	5221	14.92	5.242	7343	15.43	5.413	0.0000
Distribution of Students by (School) District (%)							
Berea	5776	0.0734	0.261	8016	0.109	0.312	0.0000
Botha-Bothe	5776	0.0682	0.252	8016	0.0828	0.276	0.0015
Leribe	5776	0.199	0.399	8016	0.178	0.382	0.0017
Mafeteng	5776	0.101	0.301	8016	0.112	0.316	0.0321
Maseru	5776	0.352	0.478	8016	0.340	0.474	0.1401
Mohale's Hoek	5776	0.0829	0.276	8016	0.0639	0.245	0.0000
Mokhotlong	5776	0.0303	0.171	8016	0.0308	0.173	0.8623
Qacha's Nek	5776	0.0156	0.124	8016	0.0147	0.120	0.6823
Quthing	5776	0.0298	0.170	8016	0.0250	0.156	0.0842
Thaba-Tseka	5776	0.00606	0.0776	8016	0.0126	0.112	0.0001
Foreign	5776	0.0424	0.202	8016	0.0314	0.175	0.0006
Distribution of Students by Faculty (%)							
Agriculture	5776	0.0571	0.232	8016	0.0586	0.235	0.7101
Education	5776	0.254	0.436	8016	0.246	0.431	0.2653
Health Sciences	5776	0.0703	0.256	8016	0.0750	0.263	0.2969
Humanities	5776	0.115	0.319	8016	0.130	0.337	0.0052
Law	5776	0.0452	0.208	8016	0.0485	0.215	0.3610
Science & Technology	5776	0.144	0.351	8016	0.124	0.329	0.0006
Social Sciences	5776	0.315	0.465	8016	0.318	0.466	0.7142

Source: Own calculations using NUL students' records data for 2010, 2011, 2012, 2013, and 2014. *Notes*: OWM is the overall weighted mean, calculated as the weighted sum of final scores of core, pre-requisite, and/or elective subject courses that make a maximum of 36 credit hours, where the weights are each course's credit hours divided by 36. The N for some variables is smaller due to missing values.

pre-FPE, and 9,610 of them post-FPE. If I exclude diploma students, there are 5,776 and 8,016 students from 230 high schools, pre- and post-FPE, respectively.

From Table 1, we can see that the pre-FPE and post-FPE periods, the OWM dropped by about 1 percentage point from 60 percent to 59 percent. The average age dropped slightly from 21.1 years old pre-FPE to 20.9 post-FPE, indicating that more young students were enrolled in the university post-FPE. This decline in average age of students could be the result of early or on-time school entry due to FPE programme.

On average, post-FPE students were of poor quality: the APS score increased from 14.9 to 15.4 points, indicating a decline in academic performance. The percentage of students passing the COSC exams with first-class statistically remained constant at about 30 percent, and that of second-class students increased 55 percent to 57 percent between these periods. The proportion of students passing with a third class dropped by about 3 percentage points. Therefore, the decline in academic performance is largely attributed to the increase in the proportion of those attaining the second-class COSC pass from 19.5 percent to 21 percent. Furthermore, this drop in performance potentially implies that, while some students attained the same pass categories pre- and post-FPE, their pass marks were towards the lower end of each pass category.

The decline in performance can also be deduced from the faculty student shares. The three faculties of Agriculture, Health Sciences, and Science and Technology have the strictest entry requirements: candidates must score high in mathematics, sciences, and english language, and have low APS score. The share of students in the faculty of Science and Technology (FOST) declined by 2 percentage points between periods. While part of the decline in FOST student share could be due to differences in student career or course tastes, it is also more likely that most students could not meet the admission requirements due to their relatively poor performance at COSC level. To further support this interpretation, data also reveals that the proportion of students admitted into diploma courses at the NUL's Institute of Extra-Mural Studies (IEMS) increased by 4 percentage points. We know that high performing students would normally go for degree programmes. Hence the increase in the proportion of students going for a diploma programme is indicative of the students' poor COSC performance post-FPE relative to pre-FPE. In sum, the table shows that there has been a drop in student performance between pre- and post-FPE.

5 Identification Strategy

In this section, I explain the semiparametric difference-in-differences (DID) identification strategy that the paper employs to tease out the long-term treatment effect of the FPE programme on academic performance (Abadie, 2005; Chang, 2020). In order to fix ideas, I begin by explaining the standard DID method (Angrist and Pischke, 2009; Blundell and Dias, 2009; Imbens and Wooldridge, 2009), assess the plausibility of its assumptions, and then explain the semiparametric

DID strategy.

5.1 The standard Difference-in-Differences method

Here I explain the standard DID strategy when repeated cross-sections data is available. Suppose student i belongs to group $G_i = g \in \{0, 1\}$ (where $G_i = 1$ is the treatment cohort), and is observed in period $T_i = t \in \{0, 1\}$ (where $T_i = 1$ is post-programme period). Let $Y_i(0)$ and $Y_i(1)$ be her potential outcomes (e.g. achievement test score) before and after the programme, respectively. Therefore, the DID estimand (or the average treatment effect on the treated (ATT)), δ_{DID}, is given by

$$\begin{aligned} ATT = \delta_{DID} &= E[Y_i(1) - Y_i(0)] \\ &= (E[Y_i|G_i = 1, T_i = 1] - E[Y_i|G_i = 1, T_i = 0]) \\ &\quad -(E[Y_i|G_i = 0, T_i = 1] - E[Y_i|G_i = 0, T_i = 0]) \end{aligned} \tag{2}$$

where $E[Y_i|G_i = 1, T_i = 1] = E[Y_{it=1}|D_i = 1, T = 1]$ is the average outcome for the treatment group unit in post-programme period. This double differencing procedure removes the bias due to permanent pre-existing differences between the two groups, and that due to common time trends unrelated to the programme. Therefore, the DID method requires that the control group should not be influenced by the programme, and should be comparable to the treatment group. In practice, the following two-way fixed effects (TWFE) linear regression model used to estimate the ATT[10]

$$Y_i = \alpha + \gamma T_i + \lambda G_i + \delta_{DID} D_i + \mathbf{X}_i \beta + \varepsilon_i \tag{3}$$

where $D_i = T_i \times G_i = d \in \{0, 1\}$ is the treatment indicator, γ is the year-specific effect common to both control and treatment cohorts; λ is a cohort-specific, time-invariant coefficient; δ_{DID} is the DID effect parameter, $\mathbf{X}_i$ is a vector of controls (current and past school- and family-supplied inputs), and ε_i is an unobserved individual error term.[11] Interacting D_i with an indicator for gender will identify the gender effects of the programme.

As mentioned earlier, the FPE programme was progressively implemented from grade 1 in year 2000 such that the first FPE cohort that successfully passed senior high school exit examinations entered the university in 2012. Given the school entry age of 6 years, the age-appropriate cohort for first, and second year(s) of university education are 18, and 19, respectively. Thus, the treatment group is defined in two ways. First, the treatment group is defined by age-group (i.e. the age-

[10]Equation 3 is an estimable version of the production function in Equation 1, where $Y_i \equiv A_i$.

[11]This TWFE model implicitly imposes further assumptions that treatment effects are homogeneous across subpopulations, and that there are no covariate-specific trends in both the treatment and control groups (Sant'Anna and Zhao, 2020).

appropriate cohort for university year 1). Second, it is defined by grade-group (i.e. whether a university student wrote primary school exit exams in 2006 or after, irrespective whether she ought to have written it earlier and be in the second year of university education). Table A.1 summarises the composition of the control and treatment groups over time.

Given that the FPE did not have age restrictions, it is inevitable that the control group under the age-appropriate cohort treatment group definition also includes the FPE treated students either because of delayed school enrolment and/or grade repetition. Higher age of school entry increases academic performance and the effect is long-lasting (Black *et al.*, 2011; Ponzo and Scoppa, 2014; Cáceres-Delpiano and Giolito, 2019). Thus, the control group's performance is likely inflated. Further, the control group could be contaminated by the potential presence of intra-household spill-over effects, whereby a younger sibling who directly benefited from FPE may have freed up some household resources to pay fees and textbooks for an older sibling in secondary education and help her to concentrate better at school. While Moshoeshoe *et al.* (2019) find no evidence of these intra-household spill over effects at the primary school level, it is possible that these spill-overs might be present at this level. The main advantage of the age-group definition is, however, that it cannot be manipulated for one to fall into any particular group. For these reasons, the DID estimand is likely biased downward, and identifies the lower bound effect of FPE.

With respect to the grade-group (year of study) treatment group definition, the treatment group is much broader as it likely includes those who delayed school enrolment, and those who repeated grades in primary school level, secondary level, and/or at university level. All those who were not covered by the no-fee policy at primary school level, but ended up being in the same grades with the FPE-treated cohort at the secondary school level and at university level are thought to be indirectly FPE-treated due to class peer effects. The control group in this case is largely clean of contamination because students are less likely skip grades. It includes all second year students, including those who are repeating the year and excluding all those who are repeating the first year. The later group, first-year repeaters, contaminate the treatment group and will likely bias upwards the performance of first years. Since the composition of the control group is similar pre- and post-FPE, there is likely to be an upward bias in FPE effect. Therefore, under this treatment group definition, the DID method likely identifies the upper bound effect of FPE.

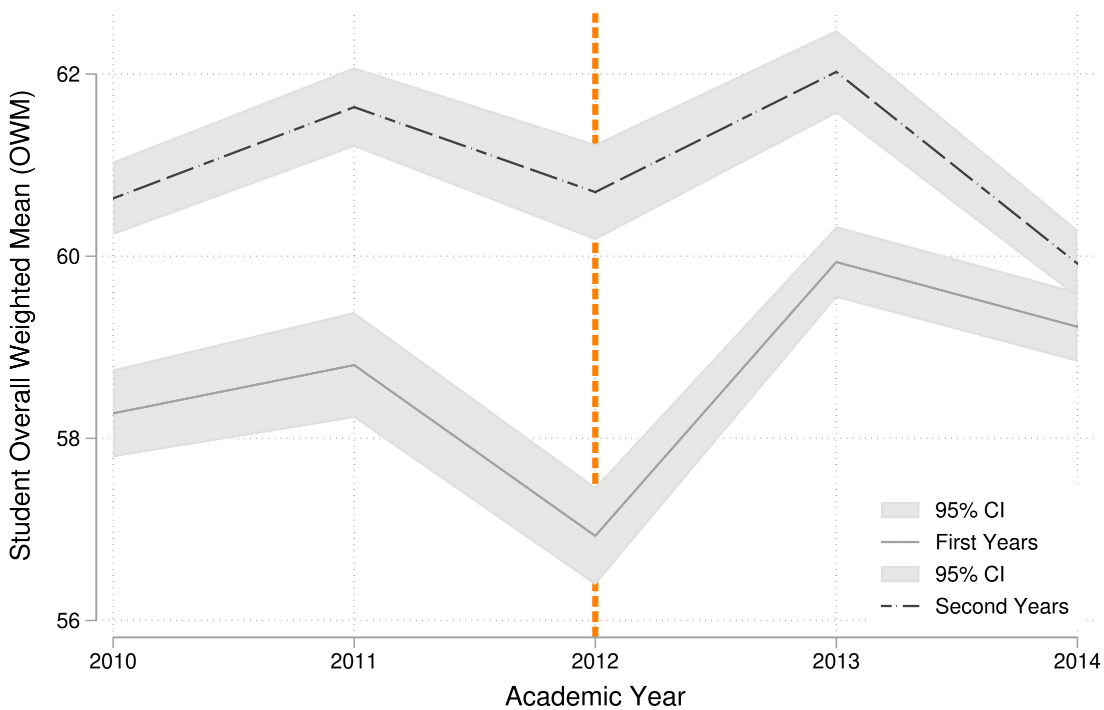
5.2 Assessing the plausibility of the parallel trends assumption

From the previous section, we know that the most important identifying assumption for the DID method is the parallel trends assumption that, in the absence of the FPE policy, the change in academic performance of the treatment group would have been equal to the to the change in academic performance of the control group. I discuss the plausibility of this assumption in this subsection. First, I assess the assumption plausibility when treatment group is defined by year of study, and then discuss it when treatment group is defined age appropriate for years 1 and 2 at university level. Lastly, I look at the compositional differences between the control and treatment groups.

5.2.1 Parallel trends in academic performances of first and second year undergraduate students

Figure 5 shows the trends in students' academic performance for the period 2010–2014. As we can see from the figure, academic performance of both first- and second-years increased between 2010 and 2011, but plummeted in 2012, the year when the first FPE cohort entered university. Since then, academic performance of first-years has recovered, surpassing the pre-FPE levels in the following years. While the gap in average performance between first- and second-years remained almost constant between 2010 and 2011, the first years' average performance dropped significantly in 2012 relative to that of the second- years (see also Table A.2). Taken together, this analysis points out that the trends in first- and second-years' academic performances were parallel before treatment (i.e. that is before the FPE cohort entered university level). This, therefore, implies that academic performance of second year students is a credible counterfactual for academic performance of first year students.

Figure 5: Trends in Students' average Academic Performance by Year of Study: 2010–2014



Source: Own calculations using the NUL students records data for the academic years 2010, 2011, 2012, 2013, and 2014. *Notes*: OWM is the overall weighted mean.

5.2.2 Parallel trends in academic performances of 16-18 year old and 19-23 year old student groups at undergraduate

I now turn to the assessment of the parallel trends assumption when the treatment group is defined as the age-appropriate cohort for the first year of university. Because of early school entry, some children do reach university before the age of 18 years. In the data, there is a small fraction of students aged below 18 years in their first year of university. While it is possible that age (i.e. date of birth) was captured incorrectly for some students in this category, there is a small fraction of students who enter the schooling system before the age of 6 years. According to MOET (2016), about 7 percent and 17 percent of children aged 16 years and 21 years and older, respectively, were in their last grade of secondary school in 2016. Therefore, I define the treatment cohort as those aged 16-18 years because they are of the appropriate age for first year of university, and those aged 19-23 years as the control cohort.

Figure 6 presents trends in students' academic performance between 2010 and 2014 by treatment cohort. We can see from the figure that the trends in academic performance of the 16-18 year olds and the 19-23 year olds are parallel throughout the period. As mentioned earlier, the control group (i.e. the 19-23 year cohort) possibly includes children directly affected by FPE. Hence, it is more than likely that the observed drop in average performance of this cohort in 2012 is largely driven by the decline in performance of fraction of old but FPE-treated children. This further supports the idea that our DID method under this treatment group definition will only identify the lower-bound effect of FPE on academic performance.

5.2.3 Compositional differences

Notwithstanding the above evidence establishing the second years and the 19-23 year old university students as the plausible counterfactuals for the respective treatment groups, compositional differences between the control and treatment groups can cause the violation of the parallel trends assumption. That is, the identifying assumption may be implausible if pre-treatment individual characteristics that are correlated with the dynamics of the outcome variable are not balanced between the FPE-treated and FPE-untreated groups (Abadie, 2005). In such a case, therefore, the FPE effect identified by the standard DID would be biased. It is, therefore, important to check whether the pre-PFE characteristics are balanced between the control and treatment groups.

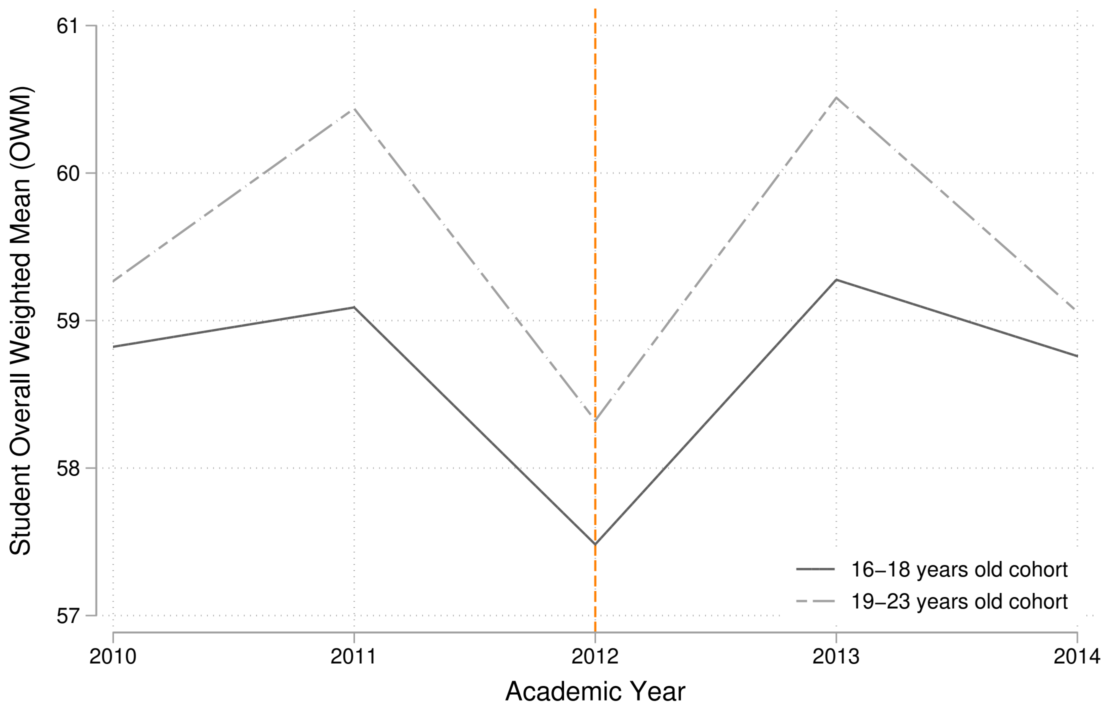
Table 2 presents the pre-FPE compositional differences between the control and treatment groups. Specifically, the table shows pre-FPE mean differences, by treatment group, in the main outcome variable (OWM) and the individual characteristics (APS, age, gender, and location). Column (3) shows the $p-$value of the $t-$test for differences in mean characteristics of the control and treatment groups pre-FPE. Looking at these $p-$values, we can see that there are statistically significant differences between the control and treatment group with respect to their age, pre-university (i.e. COSC) academic performance, gender and location (e.g. Berea and Botha-

Table 2: Pre-FPE Compositional Differences between Control and Treatment groups

Variable	Treatment (1)	Control (2)	p-value (3)	Diff ($X_1 - X_0$) (4)	Norm-diff (5)
OWM	58.5060	61.0930	0.0000	-2.5869	-0.1866
	(10.9261)	(8.5287)			
APS	19.2063	11.2710	0.0000	7.9353	1.5799
	(3.9627)	(3.0859)			
Child Age	21.3088	22.1000	0.0000	-0.7912	-0.1239
	(4.7751)	(4.2376)			
Gender (female)	0.5920	0.5651	0.0270	0.0269	0.0384
	(0.4915)	(0.4958)			
School or Home District					
Berea	0.0699	0.0817	0.0694	-0.0118	-0.0315
	(0.2550)	(0.2740)			
Botha-Bothe	0.0717	0.0573	0.0177	0.0144	0.0413
	(0.2580)	(0.2324)			
Leribe	0.1863	0.1963	0.3017	-0.0100	-0.0180
	(0.3894)	(0.3973)			
Mafeteng	0.0991	0.1005	0.8549	-0.0013	-0.0031
	(0.2989)	(0.3007)			
Maseru	0.3729	0.3579	0.2040	0.0151	0.0221
	(0.4837)	(0.4794)			
Mohale's Hoek	0.0801	0.0801	0.9988	-0.000	-0.0000
	(0.2716)	(0.2715)			
Mokhotlong	0.0304	0.0288	0.6990	0.0016	0.0067
	(0.1718)	(0.1673)			
Qacha's Nek	0.0158	0.0169	0.7214	-0.0011	-0.0062
	(0.1247)	(0.1289)			
Quthing	0.0298	0.0316	0.6736	-0.0018	-0.0073
	(0.1701)	(0.1750)			
Thaba-Tseka	0.0088	0.0066	0.3069	0.0022	0.0178
	(0.0933)	(0.0808)			
Faculty					
Agriculture	0.0374	0.0632	0.0000	-0.0258	-0.0836
	(0.1899)	(0.2434)			
Education	0.1778	0.2696	0.0000	-0.0917	-0.1566
	(0.3824)	(0.4438)			
Health Sciences	0.0541	0.0692	0.0107	-0.0151	-0.0444
	(0.2262)	(0.2538)			
Humanities	0.0758	0.1265	0.0000	-0.0507	-0.1194
	(0.2646)	(0.3324)			
Law	0.0430	0.0356	0.1275	0.0073	0.0266
	(0.2029)	(0.1856)			
Science & Technology	0.1272	0.1234	0.6346	0.0039	0.0083
	(0.3333)	(0.3289)			
Social Sciences	0.2401	0.3125	0.0000	-0.0723	-0.1147
	(0.4272	(0.4636)			
Observations	3419	3194			

Source: Own calculations using NUL students' records data for the academic years 2010, 2011, 2012, 2013, and 2014. *Notes*: OWM is the overall weighted mean. The treatment group is all students in their first year of university studies. Standard deviations are in parentheses. The reported p-values are for tests of equality of means between the treatment and control groups (independent samples). *Diff* stands for difference in means by treatment status. Norm-diff means normalized differences between treatment and control means computed as $\triangle_{\mathbf{X}} = \frac{\bar{X}_1 - \bar{X}_0}{\sqrt{S_0^2 + S_1^2}}$, where S_G^2 is the sample variance of X_i in subsample with treatment $G_i = \{0, 1\}$. $G = 1$ if a student is in second year.

Figure 6: Trends in Students' average Academic Performance by Cohort: 2010–2014



Source: Own calculations using the NUL students records data for the academic years 2010, 2011, 2012, 2013, and 2014. *Notes*: OWM is the overall weighted mean.

Bothe district).[12] Undoubtedly, these characteristics are associated with the changes in student's academic performance over time. For example, because early and current investments in human capital development are complementary, a child's high school academic performance influences her performance at university level. Given these compositional differences, Abadie (2005) proposes that the treatment effect be estimated by the semiparametric DID strategy, which allows for the distribution of both observed and unobserved characteristics to differ by treatment group. Further, the semiparametric DID method relaxes the implicit assumption in the standard DID specification that treatment effects are not heterogeneous, and it is robust to functional form misspecification as it treats the covariates nonparametrically (Sant'Anna and Zhao, 2020; Chang, 2020). Below I present this strategy as implemented in the paper.

[12]Column (5) of the table presents the normalised difference in characteristics between groups. The normalised difference between means is a scale-free measure of the difference in the distribution of characteristics by treatment status, and is given as Norm-diff $\equiv \triangle_{\mathbf{X}} = \frac{\bar{X}_1 - \bar{X}_0}{\sqrt{S_0^2 + S_1^2}}$, where S_G^2 is the sample variance of X_i in sub-sample with treatment $G_i = \{0, 1\}$. If the normalised difference is less than one quarter in absolute value, the unconfoundedness assumption is likely satisfied and the model is less sensitive to functional form (Imbens and Wooldridge, 2009). Using this indicator, we can see that pre-FPE performance at the COSC exams (pre-university entry exams) is different between groups.

5.3 The semiparametric DID strategy

Under the semiparametric DID strategy, the main identifying assumption is that, conditional on individual pre-FPE characteristics, the average performance of the FPE-treated and FPE-untreated students would have followed parallel trends in the absence of the FPE policy (Assumption 3.1, Abadie (2005)). Therefore, taking the average of the differences in change in academic performance over time between FPE-treated and FPE-untreated with similar pre-FPE characteristics allows us to identify an unbiased estimate of the ATT (δ_{SDID}) (Abadie, 2005; Sant'Anna and Zhao, 2020; Chang, 2020). This estimator requires that individuals first be matched based on their propensity score (i.e. the probability of being under FPE conditional on their pre-FPE characteristics, $\pi_0(\mathbf{X}_i) \equiv P(D=1|\mathbf{X}_i)$), before averaging the differences in outcome changes over time. In a repeated cross-sections setting, as in this study, Abadie (2005) shows that the ATT is given by

$$\delta_{SDID} = E_M\left[\frac{P(D=1|\mathbf{X}_i)}{P(D=1|)} \cdot \varphi_0 \cdot Y\right] \tag{4}$$

if $P(D=1) > 0$ and $\pi_0(\mathbf{X}_i) < 1$, where

$$\varphi_0 = \frac{T_i - \lambda}{\lambda \cdot (1-\lambda)} \cdot \frac{D - \pi_0(\mathbf{X}_i)}{\pi_0(\mathbf{X}_i) \cdot (1 - \pi_0(\mathbf{X}_i))} \tag{5}$$

Substituting φ into equation 4 gives

$$\delta_{SDID} = E_M\left[\frac{D - \pi_0(\mathbf{X}_i)}{(1 - \pi_0(\mathbf{X}_i)} \cdot \frac{\tilde{Y}}{P(D=1)}\right] \tag{6}$$

where $\tilde{Y} = \frac{T_i - \lambda}{\lambda \cdot (1-\lambda)} \cdot Y$, and λ is the proportion of post-treatment individuals in the sample.[13] Therefore, δ_{SDID} is an inverse probability weighted average of temporal changes in $\tilde{Y}$. It weighs the FPE-untreated individuals by their probability of being under FPE given their characteristics. According to Abadie (2005), if the parallel trends assumption holds unconditionally, and also conditional on the predetermined variables of interest like gender, the conditional identification can still be used to tease out the effect of treatment for different population groups. Given that the object of this paper is also to evaluate the heterogeneous effects of FPE by gender, I use the semiparametric estimator in this paper to examine the FPE policy effects on academic performance.

[13] Subscript M in the expectation sign indicates that the expectation is taken on data coming from the following mixture distribution $P_M(Y=y, D=d, X=x, T=t) = \lambda \cdot t \cdot P(Y(1)=y, D=d, X=x) + (1-\lambda)\cdot(1-t)\cdot P(Y(0)=y, D=d, X=x)$, where $\lambda \in (0,1)$.

6 Results

This section presents the estimation results of the long-run effect of FPE on student achievement. First, in Section 6.1, I present results from the non-parametric estimation of ATT ($\hat{\delta}_{DID}$) directly from equation 2. These non-parametric results are important because they are based on a framework that (1) does not impose, a priori, any functional form assumptions on the data, and (2) allows us to visualise the effect (without any controls). Second, I present, in Section 6.2, the semiparametric DID results having controlled for observed differences in individual characteristics between the control and treatment groups, and for cohort effects using age fixed effects models.

6.1 Non-parametric estimation results

Table 3 presents the non-parametric results of the long-term effects of FPE on educational achievement. Panel A shows the (lower-bound effect) results when the treatment group is defined by the age appropriate for year one of university, and panel B shows the (upper-bound effect) results when the treatment group is defined by year of study.

Table 3: Effect of FPE on Student achievement: Non-parametric results by Treatment group definition

	Pre-FPE	Post-FPE	$\Delta_{G=g}$
A: Group defined by Age-appropriate cohort			
Control group	59.9683	59.9494	-0.0189
	(0.1358)	(0.1019)	(0.1667)
Treatment group	58.9376	58.5742	-0.3634
	(0.2943)	(0.2233)	(0.3628)
ATT: $\hat{\delta}_{DID} = \Delta_{G=1} - \Delta_{G=0}$			-0.3445
			(0.3992)
B: Group defined by year of study			
Control group	61.0930	60.7804	-0.3126
	(0.1527)	(0.1332)	(0.2019)
Treatment group	58.5060	58.9179	0.4118
	(0.1898)	(0.1266)	(0.2197)
ATT: $\hat{\delta}_{DID} = \Delta_{G=1} - \Delta_{G=0}$			0.7244**
			(0.2984)

Source: Own calculations. *Notes*: $\Delta_{G=g} = E[Y_i|G_i = g, T_i = 1] - E[Y_i|G_i = g, T_i = 0]$ is time change in OWM for group $G_i = g \in \{0, 1\}$. Standard errors in parentheses and significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.

Looking at Panel A of Table 3, we can see that, pre-FPE policy, the average academic performance in the control group ($E[Y_i|G_i = 0, T_i = 0]$) and the treatment group ($E[Y_i|G_i = 1, T_i = 0]$) was, respectively, 59.97 percent and 58.94 percent. After the FPE policy implementation, the average academic performance dropped slightly to 59.95 percent in the control group ($E[Y_i|G_i = 0, T_i = 1]$), and 58.57 percent in the treatment group ($E[Y_i|G_i = 1, T_i = 1]$). However, the decline in performance over time, for the two groups respectively, is both economically and statistically insignificant. The non-parametric estimate of the average treatment effect on the treated (ATT: $\hat{\delta}_{DID} = \Delta_{G=1} - \Delta_{G=0}$) is equal to 0.34 percentage points drop in academic performance, which is not statistically significant. This, therefore, implies that the non-parametric lower bound effect of FPE on student achievement is statistically equal to zero.

Now turning to Panel B of Table 3, we can see that, pre-FPE policy, the average academic performance in the control group was 61.09 percent, while in the treatment group it was 58.51 percent. Post-FPE policy introduction, the average academic performance dropped slightly by 0.31 percentage points in the control group to stay at 60.78 percent. In the treatment group, however, student performance increased by 0.41 percentage points to 58.92 percent. While these time changes in performance within each group are both economically and statistically insignificant, the non-parametric estimate of the average treatment effect on the treated (ATT: $\hat{\delta}_{DID} = \Delta_{G=1} - \Delta_{G=0}$) is statistically significant. The ATT is equal to 0.72 percentage points, which implies that FPE increased academic performance by 0.72 percentage points. Taken together, these results indicate that the FPE effect is bounded between zero and 0.72 percentage points, at least in this non-parametric setting.

While these non-parametric results are intuitive, they may be biased by the differences in the composition of the treatment and control groups over time. One of the obvious differences between the control and treatment groups is age (see Table 2). Those in the treatment group are significantly younger than those in the control group, implying that they are from different age cohorts. If the younger cohort was in primary school during times of good economic performance, they possibly enjoyed better familial resources during their formative years compared to the older cohort. To the extent that human capital investments are more productive when made at an early stage (see Cunha and Heckman, 2009; Heckman and Mosso, 2014), the observed better performance of the treatment group is potentially due to the differences in investments (family wealth) enjoyed while young. Further, it is possible that the younger cohort was taught by young and motivated teachers in both primary and secondary school, hence their better performance in high school exit or COSC examinations (see Table 2). Therefore, the observed increase in academic performance post-FPE could actually be attributed to these factors, and not FPE. In the next Section, I estimate the FPE effect after controlling for these potential confounders. For example, I control for age fixed effects to approximate the cohort effects on performance (Cabus and De Witte, 2011).[14]

[14]The standard DID results are presented in Table A.3, and are largely consistent with the nonparametric results except that they are not statistically significant (see columns (1) and (2)).

Table 4: Long-term Effect of FPE on Educational Achievement

VARIABLES	Treatment group: First year students. (1)	Treatment group: 16-18 year olds (2)
ATT ($\hat{\delta}_{SDID}$)	1.7327***	0.4151
	(0.7714)	(0.5126)
	[0.1370, 3.3284]	[-0.5440, 1.3742]
Observations	9,274	6,127

Notes: Results produced using `DRDID` R code by Sant'Anna and Zhao (2020). Bootstrapped standard errors, with 199 replications are in parentheses. 95% Confidence intervals in brackets. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. The covariates used in the estimation of the propensity score are APS, gender, district fixed effects (FE), faculty FE, and age dummies (in the first column only) to approximate the cohort effects.

6.2 Semiparametric DID estimation results

In this section, I present the semiparametric estimates of the FPE effect after controlling for compositional differences between groups. The results are shown in Table 4. Column (1) shows results of the average effect of FPE when the treatment group is those in their first year of university (identifying the upper-bound effect), and column (2) shows results of the average effect of FPE when the treatment is those aged 16-18 years old (identifying the lower-bound effect).

Looking at column (1) of Table 4, we can see that the, having controlled for groups' compositional imbalances, the upper bound effect the FPE policy on academic achievement is 1.73 percentage points, which is statistically significant at 1 percent level. This implies that the FPE policy increased university academic performance of the beneficiaries by about 1.73 percentage points. Given the pre-FPE average performance of 59.88 percent, this increase represents a 2.9 percent increase in academic performance at the university level, which is economically significant. If we look at column (2), however, we can see that the lower bound effect of FPE on academic performance is 0.42 percentage points (or 0.7 percent), which is economically and statistically insignificant. Therefore, these results indicate that the FPE effect is effectively bounded between zero and 3 percent. It is important to note that, apart from the differences in the effect size, these semiparametric results are consistent with the non-parametric results presented above. This gives us assurance that the FPE policy did not cause a decline, but an increase, in academic performance. The results are consistent with those of Xiao *et al.* (2017) who found long lasting positive effects of a free and compulsory education program in China.

In standard deviations form, the FPE lower bound effect is 0.02 standard deviations, while the FPE upper bound effect is 0.09 standard deviations. To put these results into perspective, the short-run class size effect estimated by Fredriksson *et al.* (2013) is 0.23 standard deviations and the estimated long-run effect of free and compulsory education on maths performance by Xiao *et al.* (2017) is 0.101 standard deviations. Therefore, the upper bound effect is comparable to Xiao *et al.* (2017)'s estimate, while the lower bound is almost 11 times smaller than Fredriksson *et al.* (2013)'s estimate, for example.

Although these results indicate that FPE significantly increased students' academic performance, it is likely that they are biased. For example, they likely reflect the effect of discontinuing of the bridging programme for students into these faculties (or programmes), known as the the pre-entry science programme (PESP)[15], in 2012, which affected all students in the faculties of agriculture, health sciences, and science and technology.In the next section, I test the sensitivity of the results against this and other potential confounders.

6.3 Robustness checks

In this section, I present a number of robustness checks' results. First, I show that the results are less likely to have been driven by selection bias. Second, I present the placebo test results, using the pre-FPE data, assuming that FPE was introduced in 1999, such that the first FPE-treated cohort entered university in 2011. Third, I narrow the age window to include only students aged between 18 and 22 years old. Fourth, I present the semiparametric DID results controlling for some confounding factors, particularly the discontinuity of PESP at NUL, which affected all students doing physical science-based programmes. Lastly, I present the doubly robust DID estimates that are robust to misspecification in either the propensity score ($\pi_0(\mathbf{X}_i) \equiv P(D = 1|\mathbf{X}_i)$) or the outcome regression models for $E[Y_{it}|D = d, T = t, \mathbf{X}_i]$[16], following Sant'Anna and Zhao (2020).

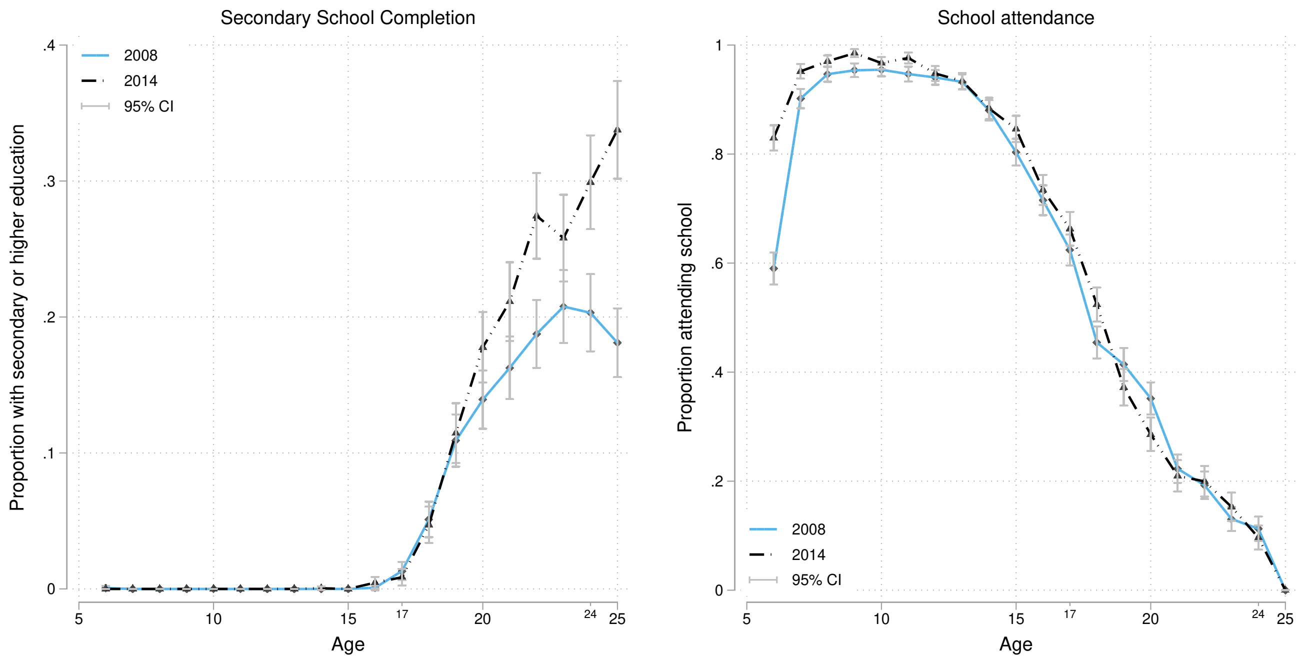
6.3.1 Who entered the university post FPE?

Given that I use university administrative data which is not representative of the population, one basic concern could be that the students who got admitted into university post FPE programme are different from those admitted pre-FPE in a number of ways. First, it could be that post FPE programme, the number of those completing secondary school and qualifying for university entrance increased. Therefore, without an increase in its capacity, the university may have admitted the best students from a larger pool of qualifying students compared to the pre-FPE period. This would overstate the real impact of the FPE programme on achievement. Second, it could be that the pre- and post-FPE cohorts that got admitted into the university differ by household wealth. Specifically, the post-FPE cohort could be poorer than the pre-FPE cohort, which would likely attenuate the FPE programme effect. Therefore, I use a nationally representative data from the

[15] I explain the PESP programme in detail below.

[16] Sant'Anna and Zhao (2020) show that the outcome regression DID estimator is given as $\hat{\delta}_{DID} = \bar{Y}_{1,1} - \left[\bar{Y}_{1,0} + n_{treat}^{-1} \sum_{i|D_i=1} \left(\hat{\mu}_{0,1}(\mathbf{X}_i) - \hat{\mu}_{0,0}(\mathbf{X}_i)\right)\right]$, where $\bar{Y}_{d,t} = n_{d,t}^{-1} \cdot \sum_{i|D_i=d,T_i=t} Y_{it}$ is the sample average outcome for treatment group d units in time t, and $\hat{\mu}_{d,t}(\mathbf{X}_i)$ is the estimator for $m_{d,t} = E[Y_{it}|D = d, T = t, \mathbf{X}_i]$.

Figure 7: School attendance and Secondary School or Higher Education Completion



Source: Own calculations using the 2008 and 2014 Lesotho Demographic Health Survey data. *Notes*: Household survey weights have been used to get the age-specific proportions.

2008 (pre-FPE period) and 2014 (post-FPE period) Lesotho Demographic Health Surveys (LDHS) in order to make sense of who actually got into university pre- and post-FPE.

The left panel of figure 7 shows the proportion of individuals who have completed secondary or higher education by age, pre- and post-FPE, and the right panel of the figure shows the enrolment rates by age, pre- and post-FPE. In 2014, the first age-appropriate FPE cohort to enter the university was aged 20 years old. We can see from the left panel of figure 7 that, pre- and post-FPE, the age-specific probability of completing secondary or higher education is statistically equal for those aged 21 and below. The right panel of the figure further shows that the enrolment rates of those aged between 14 and 24 years are statistically equal pre- and post-FPE. Taken together, this implies that the pool of potential university applicants did not increase significantly post-FPE. It is, therefore, less likely that the university could have admitted students from the very top end of the achievement distribution of all qualifying students post-FPE compared to those admitted pre-FPE.

Further, I present evidence in table 5 to show that the pre- and post-FPE cohorts do not come from different wealth groups, and even if they do, such differences would attenuate rather than overstate the FPE effect. Column (1) of the table presents the determinants of the probability of completing secondary or higher education, while column (2) presents the determinants of completed years of education. From column (1), we can see that, all else constant, the probability

Table 5: Secondary school completion and Completed years of education

	(1)	(2)
VARIABLES	Secondary Completion	Years of Education
year_{2014}	0.0058	0.4973**
	(0.0282)	(0.2398)
Household-poor (omitted = poorer)	0.0081	1.3286***
	(0.0083)	(0.1570)
Household-middle	0.0469***	2.4016***
	(0.0101)	(0.1597)
Household-rich	0.0808***	3.4853***
	(0.0125)	(0.1700)
Household-richer	0.2359***	5.0930***
	(0.0208)	(0.1992)
Household size	-0.0028**	-0.0305**
	(0.0014)	(0.0122)
female	0.0379***	2.9445***
	(0.0086)	(0.1397)
$\text{year}_{2014}\times$Household-poor	0.0046	-0.0849
	(0.0123)	(0.1629)
$\text{year}_{2014}\times$Household-middle	0.0103	-0.3457**
	(0.0140)	(0.1641)
$\text{year}_{2014}\times$Household-rich	0.0176	-0.6085***
	(0.0211)	(0.2011)
$\text{year}_{2014}\times$Household-richer	0.0323	-0.5967**
	(0.0325)	(0.2546)
female$\times$Household-poor	0.0016	-0.7557***
	(0.0108)	(0.1621)
female$\times$Household-middle	0.0122	-1.0507***
	(0.0126)	(0.1500)
female$\times$Household-rich	0.0220	-1.4964***
	(0.0144)	(0.1639)
female$\times$Household-richer	-0.0035	-2.1604***
	(0.0215)	(0.1866)
$\text{year}_{2014}\times$female	0.0291***	-0.1402
	(0.0112)	(0.1038)
Constant	-0.0455	3.9527***
	(0.0407)	(0.3609)
Observations	16,259	16,259
R-squared	0.193	0.327

Notes: Linearized (svy) standard errors in parentheses and significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. Other included controls are age dummies, location and its interaction with household wealth, gender of household head, marital status, and household relationship structure. The sample is those aged 16 to 24 years.

of completing secondary or higher education did not increase post-FPE. And the interaction of year and household wealth dummies indicates that, while household wealth increases the chances of completing secondary or higher education, the influence of household wealth did not change post-FPE. That is, pre- and post-FPE cohorts come from the same wealth groups.

From column (2), we can see that, everything held constant, 16-24 year-old children completed 0.5 more years of schooling post-FPE and those from wealthier households completed more years of schooling. However, the influence of household wealth on completed years of schooling attenuated post-FPE as indicated by the negative coefficients on year-wealth interaction dummies. The gap in completed years of education between those from rich and poor households was reduced. Consequently, if those who completed more years of education are the ones more likely to proceed to acquire higher education, the pool of students admitted into university post FPE is relatively poor compered to that admitted pre-FPE. This may have downward biased the FPE effect. Thus, taken together, the estimated effect could not have been an artefact of pre- and post-FPE differences in student composition.

6.3.2 Pre-FPE effect of FPE on student academic performance

Here I estimate the placebo FPE effect using the pre-FPE data (i.e. 2010-2011), assuming that the FPE-treated first enrolled in university in 2011. Because the FPE-treated students were not at the university in those years, we do not expect to see any positive placebo FPE effect on performance because, if there is, it would imply that the observed increase in academic performance post-FPE presented in Table 4 cannot be attributed to FPE. It would imply that academic performance is simply continuing its upward trend post-FPE. The results are reported in Table 6. Looking at results in columns (1) and (2), we can see that, pre-FPE, there was no statistically significant increase in academic performance. Taken together, these results, therefore, indicate that the observed significant increase in academic performance post-FPE is indeed attributable to FPE, not some positive time trend.

6.3.3 The narrow age range (18-22 years old sample)

Given the school entry age of 6 years, the 18 to 22 year olds are the age appropriate cohort for undergraduate university level. Further, narrowing the age range of the sample increases the chances that the treatment and control groups were in primary and high school at the same times, though in different grades. This then makes it likely that they have experienced more or less the same teacher and school resource inputs, other than no fee school attendance and free textbooks. We, therefore, can expect the FPE effects to be stronger within this age range. The results are presented in Table 7. Indeed we can see from the table that the FPE effect estimates on academic performance, in columns (1), are statistically significant and slightly larger than those reported in column (1) of Table 4 (the main results). These results indicate that the main results are not

Table 6: Long-term Effect of FPE on Educational Achievement: pre-FPE (placebo) effect

VARIABLES	(1) Treatment group: First year students	(2) Treatment group: 16-18 year olds
ATT ($\hat{\delta}_{SDID}$)	0.7139	0.2653
	(0.8515)	(0.7951)
	[-0.7990, 2.2267]	[-1.3744, 1.9049]
Observations	3,827	2,409

Notes: Results produced using `DRDID` R code by Sant'Anna and Zhao (2020). Bootstrapped standard errors, with 199 replications, are in parentheses. 95% Confidence intervals in brackets. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. The covariates used in the estimation of the propensity score are APS, gender, district fixed effects (FE), faculty FE, and age dummies (in the first column only) to approximate the cohort effects.

sensitive to sample restrictions.

6.3.4 The discontinuity of the pre-entry science programme (PESP)

The university began running the Pre-Entry Science Programme (PESP) in 1996 with the aim of bridging the knowledge gap between high school and university science and mathematics education, and ultimately enhance students' performance in science programmes. During the PESP period, all students admitted into science programmes would have to go through PESP, where they would be taught science subjects - biology, chemistry, mathematics, and physics - and English. And all those who would have completed the PESP would now proceed to enrol into what was known as the common first year of science programmes.

However, due to financial constraints, PESP was discontinued in 2012. To counter the potential negative effects of this on students' performance, the Faculty of Science and Technology, which used to run the PESP and the common first year programme, employed extra staff and extended the first year programme's academic year by two (2) weeks. These two policy shocks coincided with the entry of the first FPE cohort into the university (i.e. the FPE policy), and will likely bias the overall FPE effect on academic achievement.

Therefore, as a robustness check, I control for this potential confounding factor by removing all PESP affected students from the Faculties of Agriculture, Health Sciences, and Science and Technology, and estimate the FPE effect on academic achievement. The results are reported in table 8. We can see from this table that, similar to the main results, both the upper- and lower-bound effects of FPE are positive, and the upper-bound effect of FPE is statistically significant. It is clear, therefore, that the effect of FPE programme is not driven by the PESP discontinuity,

Table 7: Long-term Effect of FPE on Educational Achievement: Narrow age range (18-22)

VARIABLES	(1) Treatment group: First year students	(2) Treatment group: 16-18 year olds
ATT ($\hat{\delta}_{SDID}$)	3.0530***	0.4062
	(0.7659)	(0.5446)
	[1.3057, 4.8002]	[-0.6048, 1.4173]
Observations	10,032	3,943

Notes: Results produced using `DRDID` R code by Sant'Anna and Zhao (2020). Bootstrapped standard errors, with 199 replications, are in parentheses. 95% Confidence intervals in brackets. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. The covariates used in the estimation of the propensity score are APS, gender, district fixed effects (FE), faculty FE, and age dummies (in the first column only) to approximate the cohort effects.

and the resulting increase in employment and teaching time.[17]

6.3.5 Doubly Robust DID estimates

If the propensity score is misspecified, the semiparametric (inverse probability weighted) DID estimates are biased (Sant'Anna and Zhao, 2020). Therefore, to check the sensitivity of the results to potential misspecification of the propensity score, I use the Doubly Robust (DR) DID estimator proposed by Sant'Anna and Zhao (2020). Under repeated cross-section framework, as in the current case, Sant'Anna and Zhao (2020) provide the following two DR DID estimands that are consistent and locally semiparametrically efficient;

$$\delta_1^{dr,rc} = E\left[\left(\frac{D\cdot 1\{T=t\}}{E\left[D\cdot 1\{T=t\}\right]} - \frac{\frac{\pi(\mathbf{X}_i)(1-D)\cdot 1\{T=t\}}{1-\pi(\mathbf{X}_i)}}{E\left[\frac{\pi(\mathbf{X}_i)(1-D)\cdot 1\{T=t\}}{1-\pi(\mathbf{X}_i)}\right]}\right)\left(Y-\mu_{0,Y}^{rc}(T,\mathbf{X}_i)\right)\right] \tag{7}$$

and

$$\begin{aligned}\delta_2^{dr,rc} = \delta_1^{dr,rc} &+ \left(E\left[\mu_{1,1}^{rc}(\mathbf{X}_i)-\mu_{0,1}^{rc}(\mathbf{X}_i)|D=1\right] - E\left[\mu_{1,1}^{rc}(\mathbf{X}_i)-\mu_{0,1}^{rc}(\mathbf{X}_i)|D=1,T=1\right]\right)\\ &- \left(E\left[\mu_{1,0}^{rc}(\mathbf{X}_i)-\mu_{0,0}^{rc}(\mathbf{X}_i)|D=1\right] - E\left[\mu_{1,0}^{rc}(\mathbf{X}_i)-\mu_{0,0}^{rc}(\mathbf{X}_i)|D=1,T=1\right]\right)\end{aligned} \tag{8}$$

where $1\{T=t\}$ is an indicator function that equals 1 event in the braces is true, $\mu_{d,Y}^{rc}(T,\mathbf{X}_i) = T\cdot\mu_{d,1}^{rc}(\mathbf{X}_i) + (1-T)\cdot\mu_{d,0}^{rc}(\mathbf{X}_i)$, and $\mu_{d,t}^{rc}(\mathbf{X}_i)$ is the outcome regression in repeated cross-section settings.

[17] The standard DID results presented in table A.3- see columns (3) and (4) - are consistent with the results presented here.

Table 8: Long-term Effect of FPE on Educational Achievement: Without PESP-affected students

VARIABLES	(1) Treatment group: First year students	(2) Treatment group: 16-18 year olds
ATT ($\hat{\delta}_{SDID}$)	3.8587***	1.1249***
	(1.4416)	(0.4634)
	[1.3731, 6.3443]	[0.2383, 2.0115]
Observations	9,946	3,893

Notes: Results produced using DRDID R code by Sant'Anna and Zhao (2020). Bootstrapped standard errors, with 199 replications, are in parentheses. 95% Confidence intervals in brackets. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. The covariates used in the estimation of the propensity score are APS, gender, district fixed effects (FE), faculty FE, and age dummies (in the first column only) to approximate the cohort effects.

Table 9 presents the results. Panel A reports traditional DR DID estimates that are DR consistent and locally semiparametrically efficient. Panel B reports DR DID estimates that are DR consistent, locally semiparametrically efficient, and DR efficient (i.e. they are efficient under misspecification in either the outcome model, $\mu^{rc}_{d,t}(\mathbf{X}_i)$, or the propensity score, $\pi(\mathbf{X}_i)$).

We can see from panel A of the table that DR estimates are positive and statistically significant when the treatment group is defined as the first year students (the upper bound effect). For example, the results from column (1) of panel A indicate that the FPE programme increased students academic performance by between 0.37 percentage points (or 0.6 percent) and 2.97 percentage points (or 5 percent). In standard deviations, the FPE effect is bounded between 0.03 and 0.15 standard deviations. These effects are economically larger than those reported in the main results table 4.We observe the same in panel B, and the effects are even larger than those reported in table 4. Nonetheless, these results are consistent with the main results in terms of the direction of the effect.

6.4 Potential mechanisms

So far, I have not specified any possible channels through which FPE programme generates these positive effects. This section attempts to narrow down on the possible causal channels through which the observed positive effects the programme could have emerged based on figure 4 and previous research.

It is well documented in the literature that elimination of user-fees leads to an increase in access to schooling and, conditional on teacher recruitment, increases pupil teacher ratio (PTR) (see Grogan, 2009; Chyi and Zhou, 2014; Moshoeshoe *et al.*, 2019). And high PTR, especially due to an influx of poor children coming to school, leads to a decline, or at the most no change,

Table 9: Long-term Effect of FPE on Educational Achievement: DR DID estimates

VARIABLES	(1) Treatment group: First year students	(2) Treatment group: 16-18 year olds
Panel A: Traditional DR DID estimates		
ATT ($\hat{\delta}_{DRDID}$)	2.9740***	0.3726
	(0.8681)	(0.4838)
	[1.2725, 4,6755]	[-0.5757, 1.3208]
Observations	9,274	6,127
Panel B: Improved DR DID estimates		
ATT ($\hat{\delta}_{DRDID}$)	3.2793***	0.4134
	(0.5016)	(0.4579)
	[2.2960, 4.2624]	[-0.4840, 1.3109]
Observations	9,274	6,127

Notes: The point estimates of the FPE effect on achievement (OWM) and standard errors in parentheses are produced using `DRDID` R code by Sant'Anna and Zhao (2020). Bootstrapped standard errors with 199 replications are in parentheses. 95% Confidence intervals in brackets. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. The covariates used in the estimation of the propensity score are APS, gender, district fixed effects (FE), faculty/programme FE, and age dummies (in the first column only) to approximate the cohort effects. Panel A reports traditional DR DID estimates that are DR consistent and locally semiparametrically efficient. Panel B reports DR DID estimates that are DR consistent, locally semiparametrically efficient, and DR efficient (i.e. they are efficient under misspecification in either the outcome model or the propensity score).

in academic performance, holding all else constant (see Case and Deaton, 1999; Lucas and Mbiti, 2012). Similarly, building more schools, holding teacher recruitment constant, leads to an increase in access and PTR, and hence a decrease in academic achievement.

Furthermore, conditional on enrolment and teacher quality, increasing access to textbooks leads to an increase, at least not a decline, in academic achievement (see Glewwe *et al.*, 2009; Frölich and Michaelowa, 2011; Kuecken and Valfort, 2013). And the increase in teacher quality (i.e. teacher level of qualification and years of experience) can increase, but not decrease, academic achievement (Glewwe *et al.*, 2011; Harris and Sass, 2011; Chetty *et al.*, 2014).

Following the introduction of the FPE programme, there was a decline in PTR, an increase in students' textbook ownership, and an increase in teacher qualification and years of professional training (Moshoeshoe, 2015). Further, Moshoeshoe (2019) shows that academic achievement of six graders increased between 2000 (pre-FPE) and 2007 (post-FPE), and this increase was partly attributable to the fall in PTR. Therefore, the increase in teacher employment likely contributed to the increase in academic achievement at primary school level.

Taken together, therefore, it is less likely that the positive FPE programme effects documented in this paper are due to fee eliminations. The progressive implementation of the fee eliminations allowed the government to plan for the influx by recruiting more teachers and building more schools, which potentially enabled teachers to adjust their teaching strategies, as they learn, to effectively reach low-ability and/or poor students. These additional programme components, individually and in complementarity with each other, are the likely drivers of the positive FPE programme effect on academic achievement. For instance, while the school building component of the FPE programme is less likely to have contributed to the increase in academic achievement individually, it was potentially complemented by teacher recruitment and textbook provision to positively affect achievement. And because skill begets skill, this led to an increase in academic achievement at university level.

7 Conclusion

This paper examines the long-term effect of Free Primary Education policy on educational achievement, and how this varies by gender. The results indicate that the effect of FPE on educational achievement at university level is bounded between 0.42 percentage (which is statistically insignificant) and 1.73 percentage points (which is statistically significant at 1 percent).

In countries where the FPE policy was introduced simultaneously for all grades, it was found that education quality declined, at least in the short run (see Lucas and Mbiti, 2012). However, in countries where no user-fees programmes have been implemented progressively across the country, like the rural China's free and compulsory education reform programme, there are positive long-run effects on education quality (Xiao *et al.*, 2017). The results suggest that other sub-Saharan African countries that are yet to implement free education programmes can potentially increase their chances of meeting the SDG goal of inclusive and equitable education quality for all if they replicate Lesotho's FPE implementation approach. Further, these results provide important policy lessons to many countries (e.g. Tanzania) that are implementing (or contemplating to implement) free secondary or lower secondary education programmes.

This paper is not without limitations. As highlighted earlier, the FPE programme in Lesotho is a true package of supply and demand side programmes all geared towards achieving quality education for all. Therefore, while these results are interesting, they must be interpreted with caution: they do not show the effects of just fee eliminations. As we have seen in figure 3, maybe in anticipation of the influx into the secondary schooling system, secondary school resources increased from 2005. These results are partly attributable to resource increase at the secondary school level. Second, the study sample is a very select group of smart students who are potentially from rich households. Nonetheless, these results are informative in that they show how the program has affected this group.

Furthermore, I cannot completely rule out the possibility that the FPE treated group worked harder than they would have in order to compensate for the perceived lower education quality they received under FPE. That is, there could have been a Hawthorne effect. In addition to this, it is also possible that secondary school teachers may have doubled their effort when teaching the FPE cohort for the same reasons of perceived primary school education. While these are real threats to the validity of the results, nothing indicates that there has been any of these coordinated responses by students and/or teachers that could have biased the results this way. Further research is still needed to tease out the pathways through which the FPE policy increased students academic performance.

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A Appendix

Table A.1: Treatment and control group by Treatment group definition

	Pre-FPE	Post-FPE
Group defined by Age-appropriate cohort		
Control group	$(G_i = 0, T_i = 0)$	$(G_i = 0, T_i = 1)$
	(cohort: 19-23 year-olds)	(cohort: 19-23 year-olds)
Treatment group	$(G_i = 1, T_i = 0)$	$(G_i = 1, T_i = 1)$
	(cohort: 16–18 year-olds)	(cohort: 16–18 year-olds)
Group defined by year of study		
Control group	$(G_i = 0, T_i = 0)$	$(G_i = 0, T_i = 1)$
	(cohort: 2^{nd} year students)	(cohort: 2^{nd} year students)
Treatment group	$(G_i = 1, T_i = 0)$	$(G_i = 1, T_i = 1)$
	(cohort: 1^{st} year students)	(cohort: 1^{st} year students)

Source: Own representation.

Table A.2: Students' average Academic Performance by Year of Study: 2010–2014

Year	OWM (Mean)		difference	$p-$value
	$Year\ 1$	$Year\ 2$	$(year1 - year2)$	
2010	58.27	60.67	-2.40	0.0000
2011	58.81	60.64	-2.83	0.0000
2012	56.93	60.70	-3.78	0.0000
2013	59.94	62.70	-2.07	0.0000
2014	59.23	59.92	-0.69	0.0153

Source: Own calculations using NUL students' records data for the academic years 2010, 2011, 2012, 2013, and 2014. *Notes*: OWM is the overall weighted mean.

Table A.3: Long-term Effect of FPE on Educational Achievement: Standard DID results

VARIABLES	(1)	(2)	(3)	(4)
	All students		Without FOA, FOHS, and FOST students	
	Treatment group: First Year students	Treatment group: 16-18 year olds	Treatment group: First Year students	Treatment group: 16-18 year olds
ATT ($\hat{\delta}_{DID}$)	-0.1986	0.3077	0.0505	0.8722*
	(0.4127)	(0.5161)	(0.3935)	(0.5225)
First Year of study or Age-Appropriate (16-18 years)	1.9499***	0.7100	1.2837**	0.5104
	(0.5661)	(0.4347)	(0.4985)	(0.4252)
Period (Post-FPE)	-0.8578***	-0.9312***	-0.6356**	-0.7282***
	(0.2593)	(0.2140)	(0.2774)	(0.2371)
Female	1.5807***	1.4871***	2.0025***	1.9139***
	(0.2179)	(0.2155)	(0.2349)	(0.2345)
APS score	-0.5217***	-0.3983***	-0.2898***	-0.2072***
	(0.0535)	(0.0271)	(0.0374)	(0.0216)
Constant	68.3291***	66.7340***	61.0506***	59.5750***
	(0.9359)	(0.8588)	(0.9132)	(0.8310)
Observations	12,239	12,239	9,021	9,021
R-squared	0.075	0.073	0.037	0.037

Notes: FOA means Faculty of Agriculture, FOHS means Faculty of Health Sciences, and FOST means Faculty of Science and Technology. All regressions control for district, faculty, nationality of the student, age and age squared. Clustered standard errors are in parentheses, and significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1.