School quality and the performance of disadvantaged learners in South Africa

Marisa von Fintel

Abstract

In South Africa, school quality is heterogeneous and highly stratified along race, socio-economic status and geographic location. Because of the lingering effect of apartheid, public schools which historically served the white minority and received a much higher endowment of inputs are still out-performing public schools which historically served the black population. In this paper, I use longitudinal data containing test scores and background information on children in grades 3, 4 and 5 in order to estimate the effect of attending a historically white school on the test scores of black children. The models are estimated using a value-added approach in order to control for unobserved child-specific heterogeneity in the form of individual ability. I find a slightly larger effect associated with attending a former white school in South Africa than has previously been estimated for private schools in India and Pakistan and assess the validity of the estimates using various robustness checks.

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Key words: School choice, school quality, value-added models, South Africa.

School quality and the performance of disadvantaged learners in South Africa

Marisa von Fintel
Stellenbosch University*

*E-mail: marisa.vonfintel@gmail.com. Tel: +27 21 8082481. Room 507, Schumann Building, Bosman Street, University of Stellenbosch, 7600, South Africa.

1 Introduction

School quality and its impact on individuals, both in terms of their immediate cognitive development as well as their future success in the labour market, have received substantial attention from economists. In countries where school quality is heterogeneous and unequally distributed within the education system, attending a school which performs better on observed measures of quality has been found to have a significant and substantial causal effect on the academic performance of children. Examples of studies capturing this effect include those estimating the private school effect in India and Pakistan (for example, Muralidharan and Kremer, 2009; Andrabi, Das, Khwaja and Zajonc, 2011; Muralidharan, 2012 and Singh, 2013); the impact of attending an elite public school in Kenya (Lucas and Mbiti, 2014); as well as the impact of attending a charter school in the context of the United States (for example, Hanuschek, Kain, Rivkin and Branch, 2007; Hoxby and Murarka, 2009 and Angrist, Pathak and Walters, 2012).

The aim of this study is to similarly estimate the impact of school quality on the academic performance of children within South Africa. For this purpose, I make use of a panel dataset containing data on a representative sample of 266 schools in South Africa, collected as part of the National School Effectiveness Study (NSES). The NSES conducted standardised tests testing children's skills in English and mathematics when they were in grade 3 (2007), grade 4 (2008) and grade 5 (2009). It also collected background information on the learners, their households and the schools that they attended.

In South Africa, the quality of schools within the public school system is heterogeneous and highly stratified along lines of race, socio-economic status and geographic location. Large parts of the population live in geographic clusters of poverty or affluence, with access to neighbourhood schools that are of corresponding quality (Yamauchi, 2004). This emphasises the importance of school choice, especially for black children living in poor neighbourhoods (Van der Berg, 2007 and Yamauchi, 2011). The heterogeneity and stratification of school quality can be ascribed to the legacy of two historic policies. First, the policy of geographic segregation of population groups legally imposed by apartheid legislation, which caused the spatial distribution of households within the country to be racially determined and which limited the economic opportunities available to black adults. Second, the policy of institutional segregation under apartheid, which translated into racially segregated education departments administering schools.[1] The non-white education departments received considerably less funding[2] (Case and Deaton, 1999; Fiske and

[1]The department for white schools was the House of Assemblies (HOA); for coloured schools it was the House of Representatives (HOR); Indian schools were administered by the House of Delegates (HOD) and black schools were administered by the Department of Education and Training (DET). In addition, each of the homelands had a separate education department.

[2]Bhorat and Oosthuizen (2008) report that during apartheid, *per capita* spending on black schools was equal

Ladd, 2006 and Bhorat and Oosthuizen, 2008), and the schools under their management were of inferior quality compared to the schools administered by the white education department.[3]

The result of this segregation is that the school choice of many black[4] parents living in poor neighbourhoods is limited to the low quality schools available to them by virtue of the area in which they live. Those parents who are not willing to send their children to one of the low quality local schools are forced to seek alternative schools in other areas in order to escape the low quality education that is available to them. As former department of education continues to remain a significant predictor of school quality (Van der Berg, 2007), this often involves sending children to schools that were historically reserved for white children. School surveys reveal that there is a growing sub-sample of black children attending these historically white schools.[5] However, as in the case of charter schools and private schools, there is a selection issue in the choice of these schools and these children typically come from richer households than those black children who remain in schools that were historically part of the black part of the school system.

In previous studies aimed at estimating the causal effect of attending a higher-quality school, the main aim has been to deal with the non-random selection of children into these higher quality schools (be it private schools, charter schools or merely higher quality neighbourhood schools). In order to control for the selection bias inherent in the choice of school, I make use of the richness of the NSES data and control for a wide variety of child- and household-level characteristics. In addition, I make use of a value-added approach in which I include lagged test scores as a control for the unobserved learner heterogeneity in the form of past endowment and ability which would otherwise bias the estimates of the effect of attending a former white school.

I find initial estimates of an increase of 0.7 of a standard deviation on English test scores and 0.5 of a standard deviation on mathematics test scores for black children attending a former white school. These initial estimates are slightly larger than what has been estimated for India and Pakistan[6] using the same estimation strategy. However, they should be seen within the context of South Africa having one of the most divided school systems in the world. I interpret these

to just 19% of the *per capita* spending on white schools, whereas Fiske and Ladd (2006) estimate that white schools received 10 times the amount of *per capita* funding that Black schools received.

[3] The view of the apartheid government regarding education is illustrated quite succinctly by this quote from Hendrik Verwoerd, who was the Minister of Native Affairs in the 1950's: "*What is the use of teaching a Bantu child mathematics when it cannot use it in practice? That is quite absurd. Education must train people in accordance with their opportunities in life, according to the sphere in which they live*" (as quoted in Timaeus, Simelane and Letsoalo, 2013 and Fiske and Ladd, 2006).

[4] With regards to the use of the terms "white" and "black" to distinguish between the two groups, I find it useful to quote Spaull (2012, footnote 2): "*The use of race as a form of classification and nomenclature in South Africa is still widespread in the academic literature with the four largest race groups being Black African, Indian, Coloured (mixed-race) and White. This serves a functional (rather than normative) purpose and any other attempt to refer to these population groups would be cumbersome, impractical or inaccurate*".

[5] Using 2009 administrative data, in approximately 40% of the historically white schools, over half of the school population was registered as being "African".

[6] Where the impact was estimated to be in the region of 0.2 to 0.3 of a standard deviation.

results by making use of empirical evidence on the learning that takes place on a year-to-year basis in South African schools. The results translate into more than a year's worth of learning. I also address the issue of remaining unobserved individual child ability by using an instrumental variables approach and discuss the validity of this approach.

The main contribution of the paper is the fact that it examines the question of school quality within a highly unequal system. With its history of racial segregation and discrimination, South Africa is one of the most unequal societies in the world. The bimodal nature of the public school system lies at the heart of this inequality and provides an opportunity to estimate the impact of large differences in school quality on children's learning within a single public school system. Whereas most other studies in developing countries have focussed on school quality by comparing public and private schools, the focus of this paper is solely within the public school system, abstracting away from any confounding factors which may influence the choice of attending a public or private school. In addition, the results have important implications for education policy in South Africa, where estimates on the causal effect of attending a former white school provides much-needed information on separating the effect of higher quality schools from the impact of living in a wealthier household.

The rest of the paper is set out as follows. The next section provides further background on the quality of schools in South Africa and discusses some of the literature regarding school choice in the country. Section 3 describes the NSES dataset used in the paper. The fourth section provides background on value-added models and reports the estimates from the data. The fifth section deals with some remaining issues which might bias the initial results and discuss several robustness checks I conducted in this regard. Section 6 concludes.

2 School quality and inequality in South Africa

As indicated in the introduction, the consequences of historical segregation under apartheid are still visible within the highly unequal school system which operates in South Africa today, with education quality and outcomes being highly correlated with race, socio-economic status and geographic location.

The post-apartheid South African government has gone to great lengths to ensure a more equitable distribution of public funds in order to ensure that the legacy of unequal spending under apartheid is eliminated. Education funding has increased with every post-apartheid budget[7] and the funds have been allocated to the poorest schools (Fiske and Ladd, 2006). It has been

[7]The most recent budget (2013/2014) allocates R164 billion (approximately 16 US$ billion) to basic (i.e. primary and secondary) education (National Treasury of the Republic of South Africa, 2013).

estimated that the poorest 40% of households received 49% of the education spending in 2009 (Van der Berg, 2009). However, although the historical institutions enforcing the racial divide were abolished and public spending was targeted towards poor schools, the end of the apartheid system did not also herald the end of the quality divide between the former white and black parts of the system.

The result of these remaining differences in school quality can most clearly be seen in the differences in the performance of children within the two systems. Using the NSES data, I illustrate this point graphically in the figures included in the appendix to the paper, where all of the tables and figures are set out. It should at this point be noted that the NSES data include test scores from a mathematics (numeracy) and English (literacy) test. The same two tests were administered in three subsequent school years - starting with grade 3 children in 2007, then 2008 when the same children were in grade 4 and finally grade 5 in 2009. It is therefore possible to track the progress of the children in terms of their performance in these two tests over a three-year period. Looking at the kernel density curves of the distribution of the literacy and numeracy scores of black learners in the two school systems in Figure 1, it is clear how, for both numeracy and literacy, black learners attending former black schools underperform. In fact, it would appear that, for the most part, black learners in the historically white part of the school system perform better in the standardised test, written by all grades, when they are in grade 3 than a large part of the learners in the historically black part of the school system when they are in grade 5.

It is this divide which has caused the South African education system to be described as bimodal (Fleisch, 2008 and Van der Berg, 2008) and to be treated as two separate data generating processes (Van der Berg, 2008 and Taylor, 2011). Van der Berg (2008) estimates the intraclass correlation coefficient (a measure of the variance between schools as a proportion of overall variance) in South Africa to be between 0.6 and 0.7, illustrating the large differences between schools. Spaull (2012) shows how the bimodality of the South African system is not just a function of the two historic school systems, but also of school language and wealth quintiles. He also draws attention to the fact that this divide has been confirmed by all of the most recent studies conducted on South African education.[8] The ramifications of this divide extend into the labour market and create a poverty trap to those who are unlucky enough to attend a school in the wrong part of the system (see Van der Berg (2011) for further detail).

It is within this context that parents have to decide which school to send their children to. Officially, the choice of public school in South Africa is regulated by legislation, which determines the catchment area of each school and technically limits the choice of school to a geographic

[8]Including the Trends in International Mathematics and Science Study (TIMSS) in 2002, the Progress in International Reading Literacy Study (PIRLS) in 2006, and the Southern and Eastern African Consortium for Monitoring Education Quality Survey in 2007 (SACMEQ III).

area (De Kadt, 2011).[9] However, these rules are not strictly implemented and many children currently attend schools outside their immediate neighbourhood (De Kadt, 2011). Given the bimodal nature of the school system described above as well as the situation of geographic and racial divide, many poor black parents exercise what Msila (2005) describes as the "exit option" by sending their children to a school that is not within their immediate geographic area (Lemon and Battersby-Lennard, 2010). For these parents, avoiding low quality education for their children leaves them with one of two options: first, parents can follow the route of entering their children into a low-fee private school (Centre for Development and Enterprise, 2010), and second, parents can attempt to enter their children into a former white school.

The first choice has been studied most recently by Hofmeyr, McCarthy, Oliphant, Schimer and Bernstein (2013) and Schirmer, Johnston and Bernstein (Centre for Development and Enterprise, 2010), who report results from their study of private schools (or independent schools as they are referred to by the Department of Basic Education) in three of South Africa's provinces (Gauteng, Limpopo and the Eastern Cape). They conclude that the low fee private school sector in South Africa is growing rapidly, although it has not yet reached the proportions of these types of private schools elsewhere in the developing world (such as India).[10] It is estimated that approximately 6% of the schools in South Africa are private schools serving 4% of the school children in South Africa (Hofmeyr, McCarthy, Oliphant, Schimer and Bernstein, 2013). Although these low fee private schools in South Africa typically have access to fewer facilities, employ teachers who are on average less qualified and work for a lower salary, the Centre for Development and Enterprise (2010) found evidence to show that the learners in private schools performed much better in literacy and numeracy tests than the learners in public schools.[11]

Anecdotal evidence of the second option is numerous, and newspaper articles on the migration of children to other provinces for the sake of attending a former white school abound (see, for example, Gower, 2009 and Mail and Guardian, 2003). Lemon and Battersby-Lennard (2010) confirm these anecdotes with data from 10 schools in the Western Cape province where they conducted interviews with black school children who were sent away from their neighbourhood to historically coloured, Indian or white schools. From the data collected, it became clear that parental preference for higher school quality was the main impetus for movements to these other schools. These parents see access to a historically white school as a stepping stone into the

[9] School choice in South Africa is regulated primarily through the National Education Policy Act, the South Africa Schools Act, and the Employment of Educators Act. In addition, the introduction of no fee schools has also played a role (De Kadt, 2011).

[10] This is mostly attributed to the regulatory environment which complicates and subsequently inhibits the registration of private schools (Centre for Development and Enterprise, 2010), as well as the existence of historically white schools as an option.

[11] Although the robustness of these differences could not be tested, as the researchers were not able to obtain data on the background characteristics of learners in the public schools and accordingly, the study could not control or the differences in the backgrounds of the learners (Centre for Development and Enterprise, 2010).

middle class. Qualitative interviews conducted by Msila (2005) illustrate how most parents in poor black neighbourhoods would want to send their children to a better school, but are often not able to due to a shortage of cash to fund the transport to and from the school as well as pay for the school fees.

Almost 20 years after the political transition away from apartheid, South Africa's schools are more racially integrated and school-level data indicate a significant proportion of black children attending what were previously white schools (although very little racial integration has occurred in the historically black schools). Although these black children in the historically white schools are often from household with a lower socio-economic status than the white children attending these schools, it is also the case that the sub-sample of black children attending these former white schools are on average from wealthier households than their peers in historically black schools (Lam, Ardington and Leibbrandt, 2011), as will be illustrated later in this paper.

The question I wish to answer in this study is to what extent these black children in the historically white part of the school system perform better because of the improved quality of the former white schools they attend. The small size of the private school sector in South Africa, along with the large differences in quality within the public system allows me to estimate the impact of school quality within the public school system, minimising any confounding factors influencing the choice of public *versus* private schools. This can only be estimated accurately if controlling for the fact that their performance is driven, to a large extent, by the fact that they come from more affluent households. In addition, and more importantly, it is necessary to note that children attending these former white schools might not only be different based on observable characteristics, but may also differ in terms of characteristics not observed in the data, for example these children might have parents who are more likely to value education and be more motivated to ensure that their children succeed in life. In addition, these might be more motivated and more able children. In this paper, I refer to these factors collectively as "unobserved ability".

The main advantage of using the NSES data is that it provides information on outcomes and household circumstances for the same children for three years, allowing for a large number of controls and for the use of a value-added model specification. As will be discussed in Section 4 below, value-added models have in many instances been shown to provide unbiased estimates of the effect of attending a private or charter school. In addition, using such rich data allows me to estimate the heterogeneous effects of attending a former white school for different years. I however also make use of instrumental variables in order to control for any remaining bias in the value-added estimates and to check the robustness of these results.

3 Description of the data used

The data used here are from the NSES, which constitutes a panel dataset with three waves collected in 2007, 2008, and 2009. Students in 266 schools, in eight of the nine provinces of South Africa[12] were tested in literacy and numeracy at the end of the school year in grade 3 (2007), grade 4 (2008) and grade 5 (2009).[13] The median ages of sampled children in the three grades were 9, 10 and 11 years respectively. Because I am only interested in former black and former white schools, i.e. schools which existed prior to 1994, only 236 schools remain in the sample. Of these, 19 schools are former white schools and 217 are former black schools. In the estimations, I lose a further number of schools as a result of missing data. My final estimation sample therefore includes only 223 schools, of which 14 are former white schools.

The NSES was designed so as to include a nationally representative sample of schools. The sampling of the schools was done using a one-stage stratification design. Schools were selected randomly from within each of the provinces, ensuring a nationally representative sample of schools. Within each randomly selected school, the entire population of grade-specific children were included in the survey.[14]

Questionnaires regarding data at the level of the child, household and school were administered. The child and household questionnaires were answered by the children themselves. The school-level questionnaires were completed by principals and included questions on classroom size and school management practices (frequency of grade meetings, availability of lesson plans and text books). In the second and third waves, questionnaires on classroom-level characteristics were also distributed to teachers. These were mostly concerned with teacher knowledge and curriculum coverage. In addition, both the literacy and numeracy tests were administered in English to all learners in all three years. In order to facilitate comparisons over time, the same tests were administered each year.

The scores used in this study were generated from the raw scores after implementing a Rasch model, a type of Item Response Theory (IRT) model. IRT models such as the Rasch model are regularly used to standardise test scores for studying the results from education assessments. Since the same test was written in each year, an additional advantage of using IRT is that the items can be combined across years and therefore items can be ordered on one scale. The scores generated by the Rasch model were then standardised to have a mean of zero and a standard

[12] Unfortunately, the province of Gauteng (which includes Johannesburg and Pretoria) was excluded from the survey due to other testing that was being administered in that province at the same time.

[13] In South Africa, learners attend primary school from grade R (the inception year) to grade 7.

[14] The largest number of children per grade included in the survey is 256 and the smallest number of children per grade included is 4

deviation of one.[15]

The historical categorisation for each school was obtained using the master list data from the Department of Basic Education website. Since the NSES survey did not directly ask about the race of each of the learners, another method had to be employed in order to identify which learners in the sample could be classified as black and white. This process involved using the home language spoken by each of the learners as an indicator of the race of the learner. In South Africa, there is a strong correlation between race and language. More precisely, the home language speakers of the indigenous African languages are almost exclusively black individuals (in the 2011 census, 99.1% of the indigenous African language speakers were black and only 0.9% were from a different race group). There are, however, an increasing number of black individuals who speak English as their home language (in the 2011 census, this group made up approximately 2.9% of the black population). In order to maximise homogeneity between the two groups of black learners being compared in this study, I restricted the identification of black children in the sample to children who indicated their home language to be one of the indigenous African languages spoken in South Africa. In this way, I minimised the chance of incorrectly identifying non-black children as black.[16] On the other hand, this approach opens up the possibility of missing black children who speak English or Afrikaans at home. Since this group would most likely be from more affluent households and more likely to attend former white schools, their presence in the sample would most likely increase the size of the estimated differences between the two groups of children. Their omission does therefore not pose a significant problem to my analysis. At worst their omission would lead me to estimate smaller effect sizes, which may be interpreted as a lower bound.

The attrition in the sample from year-to-year is high, with just over half of the original sample (8 383 children out of an original 16 503) remaining in the sample in all three waves. The attrition for the smaller sample of black children in historically white schools seems to be somewhat lower than this, with approximately 63% of the original sample remaining at the end of the three years (225 children out of an original number of 358). The high attrition rate is not entirely unsurprising, given the frequency of drop-outs and grade repetition among black children (Branson and Lam, 2010 and Lam, Ardington and Leibbrandt, 2011) as well as the frequency of movements in between schools, specifically former black schools.[17] Since the survey did not

[15] In order to be consistent with the fact that the same tests were repeated every year, the standardisation was done using the scores from the Rasch model for 2007 for numeracy and literacy separately. This approach is suggested by Rothstein (2010).

[16] An additional sanity check reveals that this criterion to identify black children seems to be successful. Comparing the distribution of the home languages spoken by children identified as being black in the NSES with the home languages spoken by children recorded as being black and of the same age in the national census of 2011 reveals only small differences in the two distributions.

[17] Unfortunately, administrative data of the movement of children between specific schools do not exist outside the Western Cape province, where previous studies have found large movements into and out of schools (Van der

follow children but schools, I am not able to distinguish between drop-outs and repeaters on the one hand and movers on the other.

For the purpose of this study, there are two distinct groups of interest in the data, namely the black children attending historically black schools and black children attending historically white schools. However, it is also useful to consider white[18] children attending historically white schools as a third group in order to provide some context.

One would expect these three sub-samples to exhibit significant differences in observable characteristics. Table 1 in the appendix contains the mean values of the most important covariates for each of these sub-samples. What is clear from the statistics in Table 1 is that, although black children attending historically white schools are on average from wealthier households than their black counterparts in historically black schools, these children are also from households which are significantly poorer than the white children attending these historically white schools. In addition, on average, black children attending these historically white schools are also at a disadvantage in terms of the extent of their exposure to English (measured here in terms of whether they speak it at home and how often they watch English television programmes). If one uses the number of books available in the learner's home as well as parental assistance with homework as proxies for parents' education and their motivation for ensuring their children's education, the group of white children in historically white schools are on average significantly better off than the other two groups.

In terms of academic performance, black children in historically black schools perform significantly worse on average compared with the sample of black children in former white schools. White children in the former white schools however perform significantly better in both literacy and numeracy than both samples of black children.

The mean unconditional difference in test scores for the two samples of black children in both numeracy and literacy as well as the difference across years are summarised graphically in Figure 2. Without controlling for any of the differences in these two groups, the raw difference in mean test scores between black children in former white and black schools is close to 1.4 standard deviations of the pooled sample for both numeracy and literacy in all three years. The rest of the paper aims to ascertain whether this difference can causally be attributed to the impact of better school quality in former white schools.

Berg, 2007). Interestingly, these movements were not found to be systematic in the sense that they were in response to school performance or quality.

[18] These would also include a number of black children who are classified as being white because they speak English or Afrikaans as their home language. As indicated in the table, home language and socio-economic status are positively correlated and I would therefore expect the black children in this group to be from households that are significantly wealthier than their counterparts who speak one of the African languages at home. However, this is not testable since I do not have any indication of actual race in the data.

4 Value-Added Models

4.1 Background

Value-added models of learning have frequently been used to estimate the impact of teacher[19] and school quality on the academic outcomes of children. Employing these models allow for the decomposition of academic performance into attributes related to child ability[20] and school or teacher quality. Several studies which compare the estimates of teacher and school quality using value-added models to the estimates from experimental data on the same sample have recently emerged. A number of these studies find limited bias in the school quality estimates from using value-added models.

Using experimental data on assignment of teachers to classrooms in Los Angeles, Kane and Staiger (2008) test the estimates from value-added models against those using random assignment of teachers. They find that value-added models controlling for lagged student test scores and classroom characteristics produce unbiased estimates of the impact of being assigned a high quality *versus* low quality teacher. Similarly, Deming, Hastings, Kane and Staiger (2011) find that their estimates of the impact of attending a good quality neighbourhood school by using value-added models are not significantly different from the results using public school choice lottery data.

Andrabi, Das, Khwaja and Zajonc (2011) estimate the impact of private schools on test scores using first a value-added model and thereafter also employing the panel dimension of their data by specifying a dynamic GMM panel model (of the type set out in Arellano and Bond, 1991) so as to simultaneously control for measurement error in the lagged test score as well as any unobserved ability.[21] In estimating the private school effect in Pakistan, Andrabi, Das, Khwaja and Zajonc (2011) find estimates using the value-added approach and the dynamic panel GMM approach (assuming strictly exogenous inputs) that are statistically indistinguishable.

Singh (2013) estimates the private school premium in Andhra Pradesh in India using a value-added model and finds that his estimates corresponded almost exactly with the estimates by Muralidharan (2012), which were estimated using experimental data from the same cohort of children within the same geographic area.

[19] I apply the literature on classroom or teacher assignment directly to the case of school choice as the fundamental selection mechanism and accordingly the potential resulting bias would be exactly the same.

[20] Used here, as described earlier, to refer to both parental input and motivation as well as the child's own ability and motivation.

[21] Since the NSES data followed schools and not individual children, I cannot make use of these dynamic panel models.

Chetty, Friedman and Rockoff (2014a,b) ask two related questions. First, do value-added models provide estimates of the impact of teachers on the academic performance of students which are unbiased by student sorting? Second, what are the long-term impacts of teacher quality? They use US district-level data on school outcomes and teacher assignment and match these with parent characteristics and tax records of the earnings of these children after school completion to create a panel dataset covering the school and earnings history of individuals. Using data on more than 2 million US children, Chetty, Friedman and Rockoff (2014b) answer the second question in the affirmative, showing that students who were taught by better teachers, as identified by value-added models, are financially more successful later in their lives.

To answer the first question, Chetty, Friedman and Rockoff (2014a) test for bias in the value-added models by making use of parental controls as well as the exogenous changes in teaching staff. First, the authors create a measure of forecasting error by comparing predictions from the traditional value-added model to predictions from two models which are assumed to be estimated with less bias - one including parental controls and one estimated from the movements of teachers between schools. Chetty, Friedman and Rockoff (2014a) find that the bias included in traditional value-added models is small; they obtain point estimates of the bias which are indistinguishable from zero. Most importantly, Chetty, Friedman and Rockoff (2014a) single out the lagged test score as the most important control to be included in value-added models in order to reduce bias. They find that the inclusion of the lagged test score reduces the forecast bias to approximately 5%, which is statistically insignificant from zero.

However, Rothstein (2010) warns that in certain circumstances, value-added estimates of teacher quality produce biased results. Rothstein (2010) cautions that the bias resulting from selection of children into classrooms (or schools) could be significant. Including as many observed factors which may influence the selection into these schools are found to significantly reduce the bias.[22]

In this study, I address the issue of selection by including a rich set of covariates of the home background of children in the sample. Seeing that selection into these former white schools is highly correlated with the socio-economic status of the children, this approach should address some of the issues raised by Rothstein (2010). However, I also address any remaining bias in the estimates by implementing an instrumental variable approach, which is discussed below.

4.2 Estimation Framework

Following Andrabi, Das, Khwaja and Zajonc (2011), the model in Equation 1 can be specified.

[22] As indicated above, both Chetty, Friedman and Rockoff (2014a) and Kane and Staiger (2008) do not find evidence of this bias in their estimates.

$$y^*_{it} = \alpha' \mathbf{x_{it}} + \beta y^*_{i,t-1} + \delta T_{it} + \mu_{it}. \tag{1}$$

The error comprises two separate components, namely $\mu_{it} = \eta_i + \nu_{it}$. The first, η_i, is learner-specific ability which includes all unobserved characteristics of the child influencing her performance in the tests, as well as her speed of learning since it is plausible that children that come from wealthier households learn faster (Van der Berg, 2008; Timaeus, Simelane and Letsoalo, 2013). The second, ν_{it}, is the time-varying child-specific error component. As is common in the literature, I will assume that this variable is independently and identically distributed. In this model, α is referred to as the input coefficient. The parameter β is referred to in the literature as the persistence parameter and links performance across years.

In estimating β in Equation 1 using pooled OLS, there are two opposing biases that work against each other. On the one hand, omitted heterogeneity or ability, captured by η_i, could potentially bias estimates of β upwards if $cov(y^*_{i,t-1}, \mu_{it}) > 0$. On the other hand, measurement error in the test scores could potentially cause attenuation bias in the estimation of the persistence coefficient. To see why this is the case, one can write observed achievement as a function of true achievement and measurement error, as in $y_{it} = y^*_{it} + \varepsilon_{it}$ and $y_{i,t-1} = y^*_{i,t-1} + \varepsilon_{it-1}$, with $\varepsilon_{it} \sim_{iid} N(0, \sigma^2_\varepsilon)$. I assume that measurement error is not serially correlated between years. The term ε_{it} therefore captures random guessing and marking mistakes as well as errors in data capturing, but nothing more systematic than that.

Equation 1 then becomes:

$$y_{it} = \alpha' \mathbf{x_{it}} + \beta y_{i,t-1} + \delta T_{it} + (\eta_i + \nu_{it} + \varepsilon_{it} - \beta \varepsilon_{i,t-1}). \tag{2}$$

For simplicity sake, I assume that $\alpha = 0$. Now, considering only the persistence parameter, the bias associated with the measurement error, as well as the correlation between y^*_{it} and the error term can be expressed as follows:

$$\begin{aligned} plim \hat{\beta}_{OLS} &= \frac{cov(y_{it}, y_{i,t-1})}{var(y_{i,t-1})} \\ &= \beta + \left(\frac{cov(\eta_i, y^*_{i,t-1})}{\sigma^2_y + \sigma^2_\varepsilon} \right) - \left(\frac{\sigma^2_\varepsilon}{\sigma^2_y + \sigma^2_\varepsilon} \right) \beta. \end{aligned} \tag{3}$$

In Equation 3 I assume that ν_{it} and ε_{it} are both uncorrelated with the lagged test scores, $y_{i,t-1}$, since ν_{it} represents the random error component and I assume measurement error ε_{it} is not serially correlated.

The estimate of the persistence parameter will be biased upwards by the correlation between unobserved ability and downward by the measurement error. As pointed out by Andrabi, Das, Khwaja and Zajonc (2011), these two opposing sources of bias only cancel out directly if $cov(\eta_i, y^*_{i,t-1}) = \sigma^2_{\varepsilon}\beta$. Andrabi, Das, Khwaja and Zajonc (2011) show how controlling only for the measurement error in the persistence parameter without also controlling for the unobserved ability could do more harm than good. In their estimates, controlling for measurement error without a contemporaneous control for unobserved ability leads to upward bias in the estimates of the persistence parameters and attenuation bias in the estimates of the treatment variable (they also show that the pure value-added model estimation without controlling for either measurement error or unobserved ability provides unbiased estimates).[23]

I will now show how this finding may be explained within the current framework by exploring the potential bias in estimates of δ. Although the persistence parameter is of interest, the main interest of this study is in estimating δ, the treatment effect. If $\hat{\beta}$ is however biased, then $\hat{\delta}$ will also be biased. In order to break down the bias in $\hat{\delta}$, it is useful to consider imposing a biased $\hat{\beta}$ in the value-added model (Andrabi, Das, Khwaja and Zajonc, 2011). I assume that $\hat{\beta} \neq \beta$ and that the bias may be positive or negative, as set out above in Equation 3.

$$\begin{aligned} y_{it} &= (\beta - \hat{\beta})y_{i,t-1} + \delta T_{it} + \eta_i + \nu_{it} + \varepsilon_{it} - \beta\varepsilon_{i,t-1} \\ y_{it} &= \beta y_{i,t-1} + \delta T_{it} + \left[\eta_i + \nu_{it} + \varepsilon_{it} - \beta\varepsilon_{i,t-1} - \hat{\beta}y_{i,t-1}\right] \end{aligned} \tag{4}$$

The error term now contains $\hat{\beta}y_{i,t-1}$. The bias in the coefficient on the treatment variable can be broken down as follows:

$$\begin{aligned} plim\hat{\delta}_{OLS} &= \frac{cov(y_{it}, T_{it})}{var(T_{it})} \\ &= \delta + \frac{cov(\eta_i, T_{it})}{\sigma^2_T} + (\beta - \hat{\beta})\frac{cov(y_{i,t-1}, T_{it})}{\sigma^2_T} \end{aligned} \tag{5}$$

There are three points of interest here. First, estimates of attending a former white school will be upwardly biased by the fact that selection into a former white school and ability, η_i, are positively correlated with each other.

Second, since I assume that measurement error captures mostly random guessing, there is no influence on the estimates of δ arising from the presence of measurement error in test scores and lagged test scores. Although it is likely that $var(\varepsilon_{it})$ would be smaller in historically white schools than in historically black schools (as one would expect children in higher quality schools to be less likely to rely on random guessing), there is no reason to expect measurement error ε_{it} to be systematicallly correlated with T_{it}.

[23] As I show in the next section, this result holds for the NSES data as well.

Third, the term $(\beta - \hat{\beta})\frac{cov(y_{i,t-1}, T_{it})}{\sigma_T^2}$ could be positive or negative, depending on whether $\hat{\beta}$ is biased downward (i.e. $\beta > \hat{\beta}$) or upwards (i.e. $\beta < \hat{\beta}$). This will depend on the size of the terms in Equation 3 above.

Summarising, any estimate of δ would be biased (i) upward by individual child ability, and (ii) upward or downward by the bias in the estimate of the persistence parameter.

As discussed in the previous section, multiple studies have confirmed that the remaining bias in the OLS estimates of δ is not substantial, in other words that these biases do cancel out in practice provided the set of household and child controls in the model are rich enough (Evans and Schwab (1995); Andrabi, Das, Khwaja and Zajonc (2011); Deming, Hastings, Kane and Staiger (2011) and Singh (2013)). In the rest of the paper, I estimate the impact of attending a former white school using a value-added model first without controlling for measurement error and potential omitted variable bias and thereafter I use an instrumental variables approach to try and control for both measurement error and unobserved ability. The results seem to suggest that within the South African context, these two biases also cancel out.

5 Results

I start by estimating the value-added model specified in Equation 1, with a set of controls at the level of the individual child, household and provincial fixed effects. Detailed descriptions of the covariates are included in the appendix as Table 2. In my discussion I focus on the former white school coefficient, as this is the coefficient I am interested in estimating. However, throughout I also report the persistence parameter.

The output from the estimation of this baseline model is included in the appendix as Table 3. The estimated effect of attending a former white school varies with the inclusion of different controls. However including all three levels of controls (probably the most desirable specification) produces a coefficient of 0.7 for literacy and 0.5 for numeracy, being the magnitude of the premium derived by black children attending a former white school.

The sizes of these coefficients are large, and should be viewed in light of the literature on impacts of education interventions. According to Cohen (1988), an effect size of approximately 0.2 of a standard deviation should be interpreted as being small; approximately 0.5 as being medium; and in the region of 0.8 as being a large effect.

Hill, Bloom, Black and Lipsey (2008) indicate that effect sizes in educational interventions should be interpreted within the context of the intervention and in relation to empirical benchmarks such as normative expectations of what students may be expected to learn as well as empirical evidence on the speed of learning. Referring back to Figure 2 provides an indication of the size of learning for children in grades 3 to 5 - between 0.4 and 0.5 of a standard deviation on a year-to-year basis. An effect size of approximately 0.4 to 0.5 of a standard deviation would therefore approximately equal a year's worth of learning.

Taking this approach, the baseline results in the third specification of Table 3 seems to indicate more than a year's worth of learning differences between black children in former black schools and black children in former white schools, after controlling for observed household differences as well as lagged performance as a proxy of ability.

For interest sake, I also split the sample so as to estimate the impact for the children in the sample separately when they are 10 years old in grade 4 and again when they are 11 years old and in grade 5, instead of pooling the data. This provides us with a clearer understanding of how learning takes place over time. This has some interesting results which are reported in Table 4. In the first place, the impact of attending a former white school seems to diminish with time, with the persistence parameter becoming larger. This seems to indicate the divergence which takes place between the two groups of children, and the contemporaneous impact of being observed in a former white school becomes less important in determining children's test scores and the accumulation of previous input becomes more important. However, this interpretation is of course at most tentative in light of the fact that only 3 waves of data are available.

Another way of thinking about this is to view the white school effect as the intercept, with the persistence parameter as the slope of the learning curve of children in these two school systems. Table 5 reports the results from value-added models where the former white school dummy has been interacted with the persistence parameter, indicating this difference in slope between the learning curves of children in the two systems. Although the coefficient on the interaction term is statistically significant for the 2008 regression, it becomes small and statistically insignificant in the 2009 regression. There does not therefore seem to be persuasive evidence (at least for the duration of the NSES panel) of a steeper slope of learning in former white schools pointing to the fact that children in former white schools are persistently able to retain more knowledge from year to year. Evidence of this result has already been seen in the trends graphically depicted in Figure 2.

5.1 Remaining issues and robustness checks

Various concerns with the estimation strategy and the robustness of the results set out in the previous section can still be raised. This section is dedicated to discussing the most important of these concerns and trying to address these concerns by conducting various robustness checks.

5.1.1 Language policy

The first concern that I discuss here is the fact that the language policy of teaching in South African primary schools could potentially bias the results set out above. Within the current policy framework, schools have a choice to teach in the home language of the majority of the children in the school until the end of grade 3, whereafter all schools are obliged to switch to English as language of instruction (Vorster, Mayet and Taylor, 2013). The exceptions are Afrikaans schools, which are allowed to continue teaching in Afrikaans even after the end of grade 3. In the estimation sample, there are 26 schools who selected to start teaching in English from grade 1 (referred to as "straight for English" schools). Within this sub-sample of 26 straight for English schools, there are 10 former white schools and 16 former black schools. The remaining 197 schools are schools which have selected to teach in the home language of the majority of the learners in the school during grades one to 3, and then switch to English at the beginning of grade 4 (these schools are referred to as "home language" schools). Included in this sub-sample are the 4 former white Afrikaans schools.

Since the tests used as part of the NSES were conducted in English in all three years, the concern is that this discrepancy in the language of teaching will have an effect on the performance of non-English speaking children. The former white school effect estimated in the previous section could therefore just be picking up the fact that certain non-English speaking black children in former black schools were disadvantaged by the fact that they had to write the test in a language which was less familiar to them, while those black children in former white schools were advantaged because they were taught in English. This would bias the size of the former white school premium as it would include both a school quality effect as well as a language effect. In order to obtain a cleaner estimate of the effect of these former white schools on the performance of black learners, I limit the sample so that only children who have been educated in English from grade 1 are included in the estimation.

Table 6 in the appendix contains the results from these regressions which only include straight for English schools. Although the sample of black children in such schools is very small (only 1 431 children), the estimated coefficients for the impact of attending a former white school from this smaller sample are not statistically different from the original point estimates reported in Table 3. The p-value from a Wald test for the former white school coefficient being statistically significantly different from the coefficients estimated in the final specification in Table 3 is 0.4 for literacy and 0.6 for numeracy.[24]

[24] I do not estimate the same regression for the sub-sample of home language schools, as the only former white home language schools are the Afrikaans schools and there are only 4 such schools in the estimation sample, with only 63 black children in these schools.

5.1.2 Attrition

The next robustness check I conduct is to consider the high rate of attrition in the data. As discussed in Section 3, the survey was designed to follow schools and not individual children, and there is therefore no way of tracking attriting children from one wave to the next. Without further information on why children move between schools, it is unclear which of the numerous possible reasons why children would drop out of and drop into the sample from one year to the next is the correct explanation. Explanations for the high levels of attrition could include the fact that children leave weak schools to attend better schools (i.e. movement related to school choice), or because some students repeat grades and are therefore not observed in the sample in later years. However, it could also be driven by absenteeism. Overall attrition in the sample is 45%. For black children in former white schools it is 36% and for black children in former black schools it is 45%.[25]

There seems to be selective attrition based on certain characteristics, as set out in Table 7, which summarises the mean characteristics per group of attriters (i.e. children who are only observed in the data for one or two periods) versus children who remain in the data for all three years of the survey. It would appear that attriters are on average more likely to come from poorer households, attend former black schools and perform worse in both tests. Using these as well as other characteristics,[26] I estimate a probit model in order to predict the propensity of attriting for all children in the sample. I then use inverse probability weighting[27] and re-estimate the baseline regression, as reported in Table 8 in the appendix. Again, the results for the former white school effect are very close to the initial baseline results and I am unable to reject the hypothesis that the coefficient on the former white school dummy is equal to the initial estimates in the third column of Table 3.

5.1.3 Measurement error and unobserved heterogeneity

Finally, I address the two issues discussed in Andrabi, Das, Khwaja and Zajonc (2011) as set out in Section 4 above, namely measurement error and unobserved child ability. As discussed above, both these issues could bias the estimates of the former white school effect. The direction of bias

[25] The higher rate of attrition present in former black schools provides further bevidence that the results may potentially be interpreted as a lower bound, as we would expect the weakest children to be attriting from the former black schools.

[26] I include both test scores and lagged test scores for both subjects, whether the child is male, the child's age, socio-economic status, household size, exposure to English and help with homework from adults at home as controls.

[27] Inverse probability weighting involves using the inverse of the predicted propensities from the probit model as weights in a weighted least squares regression in order to control for attrition (see, for example, Andrabi, Das, Khwaja and Zajonc, 2011).

from the unobserved ability is clearly upwards, however the impact of the bias in the persistence parameter (through selection bias and measurement error) is ambiguous. As discussed in detail in Section 4, there is convincing evidence to believe that the baseline value-added estimation strategy will produce unbiased estimates of the former white school effect, as long as the covariates included in the estimation are sufficiently rich. There is therefore reason to believe that the initial results are a good indication of the impact of white schools on academic performance.

However, I also make use of two instrumental variables in order to conduct a last robustness check on the initial estimates. In the first place, I use the lagged score of the alternative subject (i.e. numeracy in the literacy regression and literacy in the numeracy regression) as an instrumental variable for measurement error in the persistence parameter. The lagged scores are highly correlated across the two subjects, making this a relevant instrument. In addition, given the nature of the measurement error I am envisaging, as described in the previous section, it is highly likely that the measurement errors in the test scores are not systematically correlated across subjects. This approach therefore seems to provide a valid instrument. Using 2SLS to correct only for the measurement error in the baseline regression, I re-estimate the initial value-added model with all of the controls and report the results in the first three columns of Table 9. As discussed in Andrabi, Das, Khwaja and Zajonc (2011), the use of an instrument to correct for the measurement error alone increases the size of the persistence parameter by correcting for the attenuation bias. However, it causes the treatment estimates to decrease, possibly leading to an under-estimation of the true size of this effect.

Looking back at Section 4, the attenuation in the treatment estimates when only controlling for measurement error in the persistence parameter is in line with what is set out in Equations 3 and 5. Correcting for the attenuation in $\hat{\beta}$ without correcting for the selection bias as a result of individual child ability would lead to $\hat{\beta} > \beta$, as set out in Equation 3. This would feed into Equation 5 to lead to a negative second term, resulting in attenuated estimates of the treatment effect, $\hat{\delta}$.

In order to correct for this bias, I also make use of an instrument to control for unobserved child ability. Since there is clear selection into the former white schools by children from wealthier households, it is easy to imagine that there could be unobserved characteristics of parents and children influencing the choice of school as well as the performance of the individual child. Since the information in the NSES data is limited, it is possible that these unobserved characteristics are not controlled for merely by including covariates in the regression as in the baseline estimation.

As indicated previously, in the current circumstances, unobserved ability could bias estimates through the effect it has on the choice of school in the following two ways. In the first place, unobserved heterogeneity at the level of the child in the form of unobserved signals of the child's inherent ability could be correlated with both the choice of school and the child's academic outcomes. More specifically, because some children have higher ability than others, it might be that parents or caregivers have high aspirations for some children and therefore send these children to former white schools. Since I do not have baseline test scores or information on the aspirations of parents for their children, I cannot control for this explicitly in the regression.[28] In the second place, bias could enter the estimation framework because of parental heterogeneity that is correlated with school choice and academic outcomes, in other words some parents or caregivers may just be more motivated than others and value education much more than other parents, irrespective of the inherent ability of their child.

Using administrative data on the exact location of each of the schools in South Africa, I am able to identify whether there are any former white schools in the neighbourhood of the children in the sample. Using the administrative data, I identify the number of former white primary schools in a 10 km radius around each of the schools in the NSES data. For most of the former black schools in the sample, there are none such alternatives in the neighbourhood. However, for 44 former black schools in the sample, there is at least one former white primary school in a 10 km radius around the school.

I restrict the sample to only include children observed in schools where there is at least one former white primary school as an alternative in the 10 km radius around the school and then re-estimate the original value-added model with all controls using 2SLS with two instruments - the lagged test score of the alternative subject for measurement error (as discussed above) and the number of former white primary schools in the 10 km radius around the school as the second instrument to control for unobserved ability. The choice of including only children in areas where there is at least one former white school in a 10 km radius is aimed at making the sample more homogenous by only taking into consideration those children who live in an area where there is a former white school close by. In other words, the parents of these children have already taken the decision to migrate or send their children to areas where there is a former white school (whereas, for the rest of the sample, there are no former white schools available in the immediate area). It should also be noted that for the current sample, the presence of a former white school in a 10 km radius is also positively correlated with socio-economic status. In other words, the sample of children living in one of the areas where there is a former white school are generally from wealthier households than those who are not (leading to a more homogenous sample, as indicated previously).

The results are set out in the last two columns in Table 9. The persistence parameters are unchanged, but the use of the second instrument increases the value of the former white school coefficient by approximately 0.1 of a standard deviation for literacy and numeracy, in line with

[28] This is the concern raised by Rothstein (2010).

what is set out in Equations 3 and 5. These estimates are not statistically significantly different from the original baseline estimates of 0.7 of a standard deviation for literacy and 0.5 of a standard deviation for numeracy.[29]

The number of former white primary schools in the 10 km radius around the NSES school is highly correlated with whether a specific child was observed in a former white school. This makes sense intuitively, as one would expect that it would be more likely for a black child to attend a former white school if there were many alternatives within driving distance from where the child lives.[30] Using this instrument I am assuming that, after controlling for socio-economic status and other proxies of household wealth and parental involvement and education, the number of white schools in the 10 km radius would not be correlated with unobserved child- and parental characteristics. This would only be violated if it is plausible that parents/households migrate specifically to an area with numerous former white schools because they value education and want their child to attend a former white school. However, since I am only including children in the sample who have been observed in areas where there is at least one alternative former white primary school as well as the fact that school choice in South Africa is not strictly regulated according to the neighbourhood in which one lives, I propose that this is a valid instrument. One drawback of this technique is the fact that it can only be done for a limited sample of children, who live in areas where there are options to attend a historically white school. Restricting the sample in this way means that I only consider only children who are from households where there are no resources or motivation to move to historically white schools (since location is not a factor).

It is useful at this point to consider the validity for the South African context of the conclusion by other authors (Evans and Schwab, 1995; Andrabi, Das, Khwaja and Zajonc, 2011 and Deming, Hastings, Kane and Staiger, 2011) that value-added models estimated using OLS provide unbiased estimates. For this purpose, I re-estimate the impact of attending a former white school on the limited sample of 3 621 children included in the 2SLS estimates controlling for both measurement error and unobserved heterogeneity. These results are reported in Table 10.

In the first two columns, I re-estimate Equation 1. It is clear that this sub-sample of children is better performing than the full sample of children. Although the persistence parameter remains in the same range as the original OLS estimates, the coefficient on the former white school dummy is significantly larger than estimated for the entire sample, at around 0.9 for literacy and 0.6 for numeracy. This might be explained by the characteristics of this specific sub-sample - I would expect the children within the former black school system to be those who because of a lack

[29]The p-value from a Wald test on the coefficient for attending a former white school in the literacy regression is 0.697 and in the numeracy regression it is 0.730.

[30]Although I do not have data on where exactly these children live, this radius tries to cover the maximum distance that most black children would travel (De Kadt, 2011).

of resources or motivation are not attending a former white school (since it is not geographic location that inhibits these children from attending a former white school). Therefore, the children in these areas who are in the former black schools are most likely weaker students, therefore explaining the larger effect size.

As expected from the discussion in Section 4, when I control for measurement error in the persistence parameter by including the lagged test score of the other subject, I find that the persistence parameter is no longer attenuated, but there is a marked decrease in the size of the coefficient on the white school dummy. In line with what previous authors have found, when controlling for individual ability as well as measurement error, the white school coefficient increases back to its original OLS level. This result confirms the conclusions by Evans and Schwab (1995); Andrabi, Das, Khwaja and Zajonc (2011) and Deming, Hastings, Kane and Staiger (2011) in the South African context and provides additional evidence for the robustness of the original value-added estimates estimated using OLS.

6 Conclusion

In South Africa, the quality of schools within the public school system is heterogeneous and highly stratified along the lines of race, socio-economic status and geographic location. Because of the lingering effect of apartheid, schools which historically served the white minority and accordingly received a much higher endowment of inputs and were subjected to different rules and regulations are still out-performing schools which historically served the black population. Attending one of these former black schools reduces the opportunity of poor black children to find employment after school and escape the poverty trap. In order to avoid these schools, many poor black parents send their children to former white schools situated outside of their immediate geographic area.

In this study I compare the difference in the performance between black learners who attend the historically white schools and those black learners who remain behind in the historically back part of the school system in order to obtain an estimate of the former white school premium. For this purpose, I have made use of the NSES longitudinal dataset which contains data on learner, household and school level characteristics of learners in both school systems in grades 3, 4 and 5. In order to estimate this effect, I make use of a value-added model and find an impact of 0.5 of a standard deviation for numeracy and 0.7 of a standard deviation for literacy. I conduct a number of robustness checks and discuss some of the factors which may potentially be biasing the results, including the language policy in these primary schools, attrition in the data, measurement error in the test scores and unobserved ability which may be biasing the results.

In all of the robustness checks, I find estimates that are within the same range as the estimates in the baseline regression. Although the size of these effects are somewhat larger than what has been estimated for other developing countries such as Pakistan and India, their size should be seen within the context of South Africa being one of the countries with the most unequal education system in the world.

The results also illustrate the large impact that school quality can have on the academic performance of children, which is separate from the impact of household circumstances. The advantage of examining the question of school quality within a country such as South Africa is that it provides an opportunity to examine the impact of school quality as a question contained within the public school system.

I also find additional evidence for the fact that the original OLS estimates are unbiased in the South African context by confirming the results from Andrabi, Das, Khwaja and Zajonc (2011) and others. I show that the original estimates from the value-added model using OLS are almost identical to the estimates from the 2SLS model where both measurement error (which attenuates the coefficients) and unobserved heterogeneity (which biases the coefficients upward) are controlled for.

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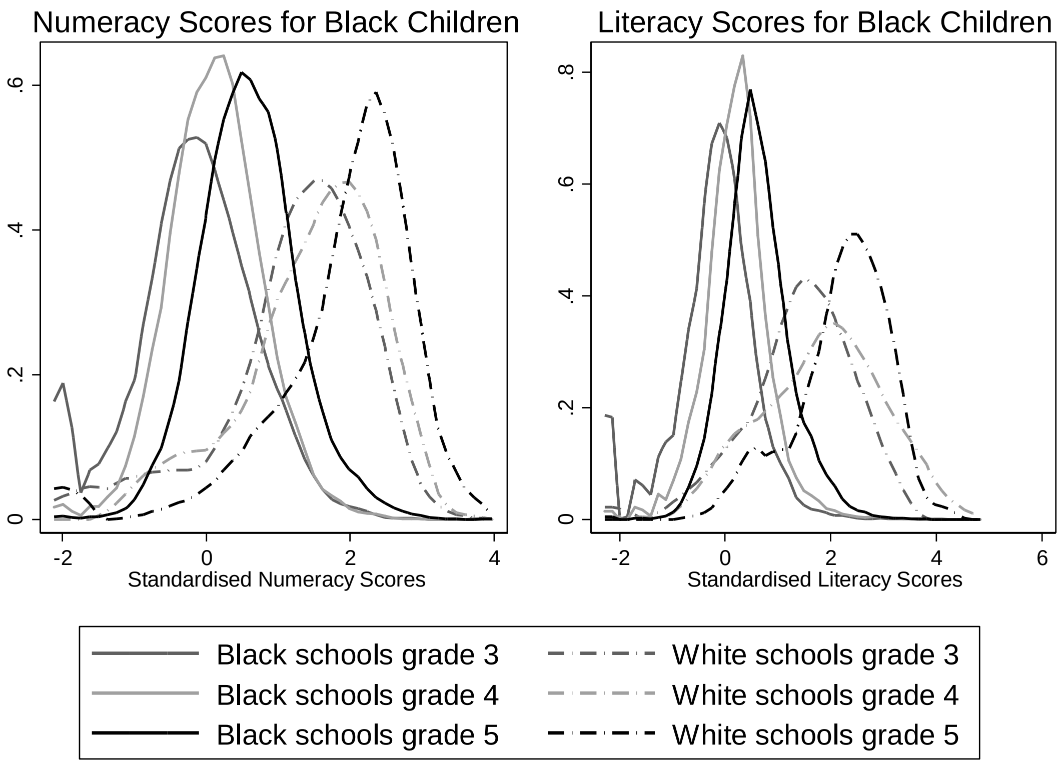
Appendix

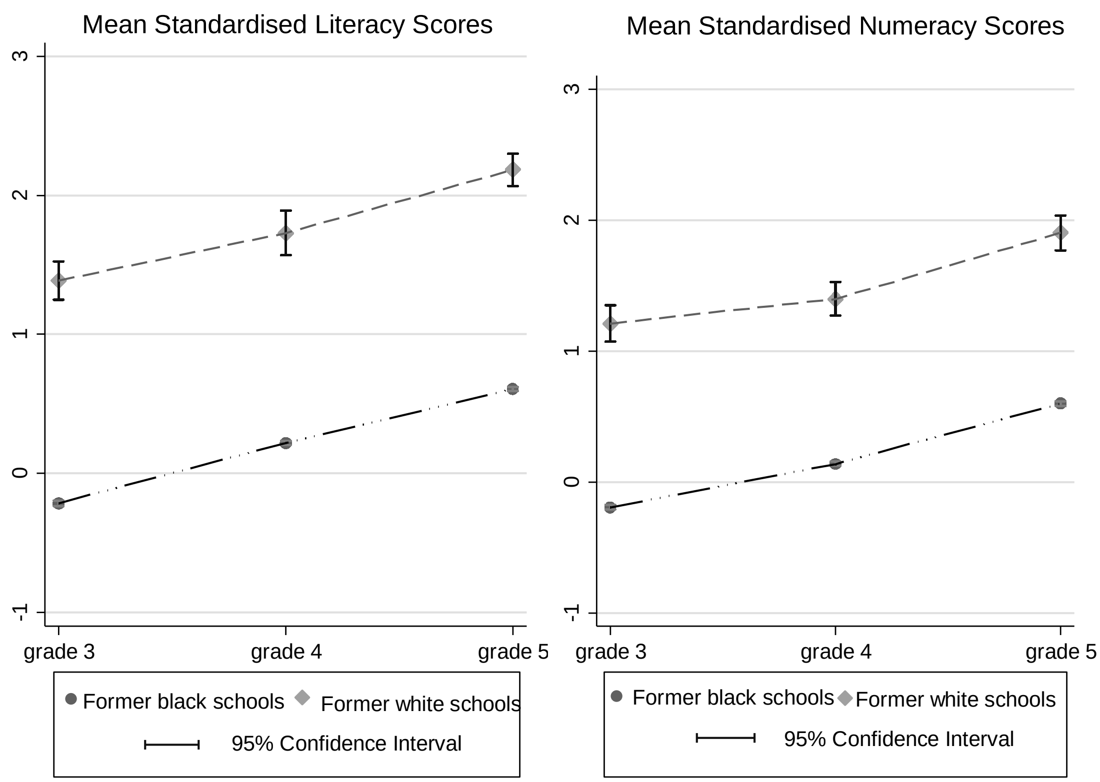
Figure 1: The performance of black children in the two school systems



Source: NSES data (2007, 2008, 2009).

Notes: Includes all black children who remained in the sample for all three waves.

Figure 2: Unconditional differences in standardised test scores of black children



Source: NSES data (2007, 2008, 2009).

Notes: Sample includes only black children who remained in the sample for all three waves. Weighted mean standardised test scores (mean=0, standard deviation=1). 95% Confidence intervals reported (not visible for sample of former black schools).

Table 1: Descriptive statistics - differences between three groups (pooled data from 2007 to 2009)

	Black children in former white schools°	Black children in former black schools°	White children in former white schools°°
Mean home SES	0.973	-0.183*	1.424*
Proportion male	0.512	0.470	0.440*
Age in years	10.418	10.799*	9.830*
Proportion living in house with 4+ siblings	0.248	0.468*	0.054*
Proportion speaking English 4+ times per week at home	0.348	0.073*	0.444*
Proportion exposed to English on TV 4+ times per week	0.762	0.407*	0.770
Proportion receiving help with homework from parents	0.757	0.505*	0.792*
Proportion with >50 books in their home	0.306	0.083*	0.544*
Mean numeracy score	1.677	0.383*	1.948*
Mean literacy score	1.979	0.428*	2.149*
Number of observations	428	12 539	1 170

Source: NSES data (2007, 2008, 2009).

Notes: °Descriptive statistics of children included in estimation sample. °° Descriptive statistics of children included in data (not in estimation sample).* Indicates that the difference between black learners in historically white schools and historically black schools is significant at the 5% level (3rd column) and the difference between black and white learners in historically white schools is significant at the 5% level (4th column).

Table 2: Description of covariates

Variable name	Description
Child level controls	
male	=1 if child is male and =0 if child ifs female.
actual_age	Age of the child in years.
actual_age2	Age of the child in years squared.
Household level controls	
ses	Household socio-economic status (SES). Using multiple component analysis, the household socio-economic status was derived using data on a list of eight household amenities and assets which were either present in the household or not (based on the survey completed by each learner). These are: electricity, tap water, flush toilet in the dwelling, car, computer, daily newspaper, fridge, washing machine.
ses2	ses squared.
hhsize_big	Child lives in a household with four or more siblings.
read_adult_never	The child never reads with an adult at home.
read_adult_1to3	The child reads with an adult at home 1 to 3 times a week on average.
read_adult_4plus	The child reads with an adult at home 4 times or more per week on average.
speak_never	The child never speaks English at home.
speak_1to3	The child speaks English at home 1 to 3 times per week on average.
speak_4plus	The child speaks English at home 4 times or more per week on average.
tv_never	The child never watches English television at home.
tv_1to3	The child watches English television 1to 3 times per week on average.
tv_4plus	The child watches English television 4 times or more per week on average.
nohelp	The child receives no help from an adult at home with homework.
help_parents	The child receives help from parents at home with homework.
help_other	The child receives help from other adults(s) (not his/her parents) at home with homework.
books_0	No books at home.
books_1to10	One to ten books at home.
books_10to50	Ten to fifty books at home.
books_50plus	Fifty books or more at home.
Provincial controls	
prov1	Eastern Cape
prov2	Free State
prov3	KwaZulu Natal
prov4	Limpopo
prov5	Mpumalanga
prov6	North West
prov7	Northern Cape
prov8	Western Cape

Table 3: Baseline value-added model (pooled OLS)

	Literacy			Numeracy		
	1	2	3	1	2	3
Former White School	0.831***	0.693***	0.699***	0.574***	0.461***	0.465***
	(0.1507)	(0.145)	(0.133)	(0.115)	(0.113)	(0.104)
Persistence	0.474***	0.450***	0.437***	0.547***	0.535***	0.524***
	(0.025)	(0.023)	(0.021)	(0.019)	(0.017)	(0.017)
N	12 967	12 967	12 967	12 967	12 967	12 967
Clusters	223	223	223	223	223	223
R-squared	0.422	0.444	0.451	0.437	0.455	0.465
F-stat	154.263	65.001	59.646	226.51	90.803	94.052
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household Controls	No	Yes	Yes	No	Yes	Yes
Provincial Controls	No	No	Yes	No	No	Yes

Source: NSES data (2007, 2008, 2009).

Notes: OLS regression coefficients with standard errors (clustered at school level). Sample includes only black learners who were observed in all three waves and who attended one of 223 schools in estimation sample. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Table 4: Value-added model per grade

	Literacy		Numeracy	
	Grade 4 (10 years)	Grade 5 (11 years)	Grade 4 (10 years)	Grade 5 (11 years)
Former White School	0.925***	0.4881***	0.689***	0.226***
	(0.222)	(0.072)	(0.142)	(0.126)
Persistence	0.293***	0.574***	0.372***	0.709***
	(0.026)	(0.020)	(0.022)	(0.019)
N	6 620	6 347	6 620	6 347
Clusters	223	223	223	223
R-squared	0.366	0.549	0.391	0.577
F-stat	50.800	113.125	34.850	120.510
Individual controls	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes
Provincial controls	Yes	Yes	Yes	Yes

Source: NSES data (2007, 2008, 2009).

Notes: OLS regression coefficients with standard errors (clustered at school level). Sample includes only black learners who were observed in all three waves and who attended one of 223 schools in estimation sample. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Table 5: Value-added model per grade with interaction effects

	Literacy		Numeracy	
	Grade 4 (10 years)	Grade 5 (11 years)	Grade 4 (10 years)	Grade 5 (11 years)
Former White School	0.446*	0.610***	0.427***	0.180
	(0.231)	(0.171)	(0.144)	(0.2898)
Persistence	0.274***	0.581***	0.361***	0.707***
	(0.025)	(0.020)	(0.022)	(0.019)
Former White School*Persistence	0.378***	-0.073	0.236***	0.033
	(0.127)	(0.072))	(0.071)	(0.130)
N	6 620	6 347	6 620	6 347
Clusters	223	223	223	223
R-squared	0.375	0.549	0.394	0.577
F-stat	51.252	176.127	60.858	117.787
Individual Controls	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Provincial Controls	Yes	Yes	Yes	Yes

Source: NSES data (2007, 2008, 2009).

Notes: OLS regression coefficients with standard errors (clustered at school level). Sample includes only black learners who were observed in all three waves and who attended one of 223 schools in estimation sample. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Table 6: Language policy estimating impact in straight for English schools

	Literacy	Numeracy
Former White School	0.519**	0.384**
	(0.203)	(0.161)
Persistence	0.460***	0.494***
	(0.049)	(0.047)
N	1 431	1 431
Clusters	26	26
R-squared	0.724	0.696

Source: NSES data (2007, 2008, 2009).

Notes: OLS regression coefficients and standard errors (clustered at school level). Specifications include all controls. Sample includes only black learners who were observed in all three waves and attended a straight for English school. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Table 7: Describing the attriters

Covariate	Observed in only one or two waves	Observed in all three waves
Mean home SES	-0.028	0.024*
In former white school	0.066	0.084*
Black	0.841	0.837
Age in years	10.591	10.270*
Mean numeracy score	0.203	0.532*
Mean literacy score	0.391	0.755*

Source: NSES data (2007, 2008, 2009).

Notes: Sample means per group. * indicates that the difference between the attriters and those children who remained in the panel is significant at the 5% level.

Table 8: Value-added model controlling for attrition using inverse probability weighting

	Literacy	Numeracy
Former White School	0.652***	0.419***
	(0.187)	(0.143)
Persistence	0.396***	0.491***
	(0.022)	(0.018)
N	12 967	12 967
Clusters	223	223
R-squared	0.402	0.427
F-stat	40.587	85.752

Source: NSES data (2007, 2008, 2009).

Notes: WLS regression coefficients with standard errors (clustered at school level) including all controls. Weights used are inverse probability of not remaining in the sample for all three waves. Sample includes only black learners who were observed in all three waves and attended one of the 223 schools in the estimation sample. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Table 9: Value-added model controlling for measurement error and unobserved heterogeneity

	Controlling for measurement error		Controlling for measurement error and unobserved heterogeneity	
	Literacy	Numeracy	Literacy	Numeracy
Former White School	0.441***	0.289***	0.835***	0.523***
	(0.100)	(0.089)	(0.338)	(0.243)
Persistence	0.628***	0.670***	0.626***	0.685***
	(0.031)	(0.029)	(0.096)	(0.072)
N	12 967	12 967	3 621	3 621
Clusters	223	223	44	44
R-squared	0.415	0.443	0.573	0.565
First stage F-statistic (persistence)	786.31	710.62	354.63	208.44
First stage F-statistic (former white school)	-	-	27.22	30.27

Source: NSES data (2007, 2008, 2009).

Notes: 2SLS regression coefficients with standard errors (clustered at school level). Instrument for persistence parameter is the lagged test score of the other subject. Instrument for unobserved heterogeneity is the number of former white primary schools in a 10km radius around the school in which the child is observed in the sample. The sample includes only black learners who were observed in all three waves and for second specification the sample is also limited to children in areas with at least one former white primary school in a 10 km radius. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

Table 10: Value-added model controlling for measurement error and unobserved heterogeneity (limited sample)

	Pooled OLS (no instruments) on limited sample		2SLS Controlling for measurement error		2SLS Controlling for measurement error and unobserved heterogeneity	
	Literacy	Numeracy	Literacy	Numeracy	Literacy	Numeracy
Former White School	0.857***	0.577***	0.422***	0.230***	0.835***	0.523***
	(0.121)	(0.089)	(0.124)	(0.094)	(0.338)	(0.243)
Persistence	0.450***	0.523***	0.702***	0.743***	0.626***	0.685***
	(0.037)	(0.023)	(0.063)	(0.052)	(0.096)	(0.072)
N	3 621	3 621	3 621	3 621	3 621	3 621
Clusters	44	44	44	44	44	44
R-squared	0.599	0.586	0.557	0.552	0.573	0.565
First stage F-statistic (persistence)	-	-	233.16	289.69	354.63	208.44
First stage F-statistic (former white school)	-	-	-	-	27.22	30.27

Source: NSES data (2007, 2008, 2009).

Notes: 2SLS regression coefficients with standard errors (clustered at school level). Instrument for persistence parameter is the lagged test score of the other subject. Instrument for unobserved heterogeneity is the number of former white primary schools in a 10km radius around the school in which the child is observed in the sample. The sample includes only black learners who were observed in all three waves and for second specification the sample is also limited to children in areas with at least one former white primary school in a 10 km radius. * Significant at the 10% level **Significant at the 5% level ***Significant at the 1% level

The **Research Project on Employment, Income Distribution and Inclusive Growth (REDI3x3)** is a multi-year collaborative national research initiative. The project seeks to address South Africa's unemployment, inequality and poverty challenges.

It is aimed at deepening understanding of the dynamics of employment, incomes and economic growth trends, in particular by focusing on the interconnections between these three areas.

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Collaboration with researchers at universities and research entities and fostering engagement between researchers and policymakers are key objectives of the initiative.

The project is based at SALDRU at the University of Cape Town and supported by the National Treasury.

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Research Project on Employment, Income Distribution & Inclusive Growth

Towards an integrated response to unemployment, inequality and poverty