WORKING PAPER / 2024.07

Beware the gambit
The effects of teacher allocation on learning achievement in Senegalese primary schools

Oswald **Koussihouede**
Sahawal **Alidou**
Damase **Sossou**

University of Antwerp
IOB | Institute of Development Policy

The IOB Working Paper Series seeks to stimulate the timely exchange of ideas about development issues, by offering a forum to get findings out quickly, even in a less than fully polished form. The IOB Working Papers are vetted by the chair of the IOB Research Commission. The findings and views expressed in the IOB Working Papers are those of the authors. They do not necessarily represent the views of IOB.

Institute of Development Policy

Postal address:	Visiting address:
Prinsstraat 13	Lange Sint-Annastraat 7
B-2000 Antwerpen	B-2000 Antwerpen
Belgium	Belgium

Tel: +32 (0)3 265 57 70
Fax: +32 (0)3 265 57 71
e-mail: iob@uantwerp.be
http://www.uantwerp.be/iob

WORKING PAPER / 2024.07

ISSN 2294-8643

Beware the gambit*
The effects of teacher allocation on learning achievement in Senegalese primary schools

Oswald **Koussihouede**
Sahawal **Alidou**
Damase **Sossou**[1]

September 2024

* In chess, a gambit occurs when a player sacrifices material during the opening to gain some form of compensation. We use this image to illustrate the trade-off between education quality and equity observed in all teacher allocations tested in this paper.

[1] Oswald Koussihouede is a Senior Education Policy Analyst and Planner at UNESCO's International Institute for Educational Planning. Sahawal Alidou is Research Economist at the African Development Bank and Damase Sossou is a Principal Evaluation Capacity Development Officer at the African Development Bank. The authors express their gratitude to Esther Yoon for her excellent research assistance and to George Marbuah, Patrick Nkengne, and Polycarp Otieno for their valuable comments on earlier versions of this paper. Corresponding email: s.alidou@afdb.org.

University of Antwerp
IOB | Institute of Development Policy

Beware the gambit*: The effects of teacher allocation on learning achievement in Senegalese primary schools

Oswald Koussihouede, Sahawal Alidou and Damase Sossou[1]

September 2024

Abstract

The quality of education in Sub-Saharan Africa continues to be generally low, with existing research indicating an ongoing "learning crisis". Some key dimensions of the issue of education quality in SSA relate to the availability and the (mis) allocation of teachers within countries. Drawing on the literature on the role of Information, Communication and Technology in improving public service delivery and promoting transparency, this study investigates how a data-driven and ICT-based allocation of teachers can be used to improve quality and equity in primary education. To do so, we use machine-learning techniques to assess the distributional effects of various teacher transfer mechanisms on students' learning outcomes in primary education in Senegal. Our results suggest that the average performance of students improves in all 12 simulations tested, but at the expense of equity. These results highlight a trade-off between quality and equity, which should be further explored and considered in the search for an "optimal" teacher assignment mechanism in primary education in Senegal. Furthermore, a comparison across the 12 simulations, based on a ratio defined as the equity cost for a one-unit improvement in quality, suggests that regional-level teacher transfer schemes are more effective than the national-level ones in reconciling quality improvement with the need to minimize educational inequality in primary education system in Senegal.

Classification: I20, I24

Key words: education quality and equity, primary education, teacher allocation, machine learning.

---

* In chess, a gambit occurs when a player sacrifices material during the opening to gain some form of compensation. We use this image to illustrate the trade-off between education quality and equity observed in all teacher allocations tested in this paper.

[1] Oswald Koussihouede is a Senior Education Policy Analyst and Planner at UNESCO's International Institute for Educational Planning. Sahawal Alidou is Research Economist at the African Development Bank and Damase Sossou is a Principal Evaluation Capacity Development Officer at the African Development Bank. The authors express their gratitude to Esther Yoon for her excellent research assistance and to George Marbuah, Patrick Nkengne, and Polycarp Otieno for their valuable comments on earlier versions of this paper. Corresponding email: s.alidou@afdb.org.

1 Introduction

Despite substantial progress in the past two decades in terms of access to education, Sub-Saharan Africa (SSA) still has the highest rates of education exclusion with over one-fifth of primary-age children and 60 percent of 15-17 aged adolescents out of school in 2020.[2] For the ones in school, quality of education remains poor and learning outcomes and educational achievement still depend on factors including children's gender, family background, and disability status. Furthermore, existing research has shown that children are in school but not learning (situation referred to as 'the learning crisis') and that "education systems in many SSA countries are aligned for different purposes, except learning".[3]

A key factor explaining low quality of education in SSA is the availability and the quality of teachers employed in the education system. Teachers indeed represent the most influential input to improving students' learning outcomes (Chetty, Friedman & Rockoff, 2014; Rivkin, Hanushek & Kain, 2005) as well as their noncognitive skills (Jackson, 2018), particularly for the most disadvantaged students (Araujo et al., 2016). The main drivers of teacher shortages in SSA are rapid education expansion, increased financial pressure on education budgets, insufficient teachers' preparation, and qualification, but also difficult working conditions, poor social support, and lack of respect for teachers (Education 2030 Closing the gap). The proportion of qualified teachers in primary education in SSA declined from 84% in 2000 to 69% in 2019,[4] and the region will need to recruit 15 million teachers by 2030 to reach the Education 2030 goals. In addition to the problem of shortage, (qualified) teachers are often misallocated within countries, reinforcing existing educational inequalities, and more specifically those between urban and rural areas, the latter being the most underserved. With the education expenses going mainly to teacher salaries,[5] this misallocation also impedes on the public spending efficiency in primary education in these countries where resources remain largely constrained. Recruiting and retaining qualified teachers in remote and rural areas is therefore an important challenge to education systems (Buckler, 2011; Mafora, 2013; du Plessis & Mestry, 2019) in the countries of SSA.

Depending on the country, assignment of teachers is done at the central level, at the decentralized level, or via a "market system" whereby teachers are not sent to schools but apply for posts in specific

[2] https://blogs.worldbank.org/developmenttalk/high-price-education-sub-saharan-africa.

[3] https://riseprogramme.org/blog/three-issues-sub-saharan-africa-educational-development.

[4] UNESCO Institute for Statistics, https://uis.unesco.org, last consulted on September 4, 2023.

[5] More than 90% in many countries. Ibid.

schools (Lewin, 2000). Following their initial appointment, teachers may change schools for a variety of reasons, including but not limited to promotion, personal request, or disciplinary action/punishment. These movements may affect education quality and existing education inequalities one way or the other. They may also serve as (de)motivation scheme for teachers depending on their purpose and whether they are done in a fair and transparent manner. In any case, when based on criteria other than teacher's merit and system rationalization, transfers between positions − which this paper is concerned with − are subject to rent-seeking and patronage practices, and lead to situations whereby teachers invest their time and energy in moving out or staying in a preferred location, contributing to reinforce existing hierarchies in schools and education inequalities (Ramachandran et al., 2017).

Drawing on the literature on the role of Information, Communication and Technology (ICT) and digitalization in improving public service delivery and promoting transparency (e.g., Adam & Fazekas, 2021; Elbahnasawy, 2021; Haruna & Alhassan, 2022; Muralidharan et al., 2016), particularly in the education system (Elacqua et al., 2022), this paper investigates how data-driven and ICT-based allocations of teachers can be used to improve quality and equity in primary education. To do so, we use machine learning techniques to assess the distributional effects of several teacher transfer simulations on student learning outcomes in Senegalese primary schools. The simulations involve random allocations and allocations based on teachers' competences and experience, both at the regional and the national levels. The focus on Senegal is motivated by its significant experience with data-driven and ICT-based systems for managing the teaching workforce[6] as well as its low pupil-to-teacher ratio combined with the highest proportion of qualified teachers in Francophone Africa, which render the issue of teacher transfer and allocation most relevant to the country.[7] Additionally, the availability of teachers' scores from the 2019 PASEC[8] international assessment further supports this focus.

In the paper, we simulate 12 allocation mechanisms using De Luca et al. (2023)'s weighted average least squares (WALS). Overall, none of our 12 simulations is a first best in the sense of improving both quality and equity of the education system. They all improve education quality (measured by the

[6] Senegal was among the first countries to implement a data-driven and ICT based-allocation of teachers in SSA in 2013 with a system is called MIRADOR. As a comparison, the Rwandan Teacher Management Information System was introduced in 2013 but officially launched only in 2021, and similar systems are being implemented in Burkina Faso (as from 2020), Togo (2022), DRC (2023), Madagascar (2023) and Chad (expected in 2025).

[7] In Senegal, the pupils per teacher ratio is of 35 compared to an average of 42 in PASEC countries and an international accepted standard of 40; and the proportion of qualified teachers is 99.9% in 2022 (Alidou & Koussihouede, 2024).

[8] PASEC stands for Program for the Analysis of Education Systems of the CONFEMEN (Conference of Ministers of Education of French-speaking States and Governments).

mean of student scores) but at the cost of a decreased equity (proxied by the standard deviation of student scores). This suggests the existence of a trade-off between quality and equity which requires policymakers' attention in the search of an "optimal" allocation and transfer of teachers in primary education in Senegal. A ranking of the 12 simulations based on a ratio defined as the equity cost of per unit improvement of quality shows that regional level teachers' assignment schemes are more suitable in the context of Senegal. Perhaps most striking is the fact that, in addition to increase inequality, all 12 simulations (including assignment of high-quality teachers to low-performing classrooms) seem to negatively impact students at the bottom of the distribution of scores, reflecting the need to better tailor teaching and curriculum to students' level.

To the best our knowledge, this paper is among the firsts using machine learning to assess whether education quality and equity can be improved with alternative allocations of the existing "stock" of teaching capacities in primary education in Africa. It departs from studies that account for preferences and/or beliefs and use *deferred acceptance* and *immediate acceptance* mechanisms (e.g., Abdulkadiroğlu & Sönmez, 2003), or *strategy-proof* mechanisms (Arteaga et al., 2022; Combe et al., 2022) which are commonly adopted in the field of *education market design* (Akbarpour et al., 2022; Rees-Jones and Shorrer, 2023) to identify "optimal" teachers' allocation. It rather considers teacher transfer as a central planner optimization problem in which transparent rules and criteria are applied to obtain an allocation that maximizes the education system efficiency, similar to centralized teacher assignment in Singapore and South Korea (Elacqua, Olsen & Velez-Ferro, 2021). In doing so, our reflection does not account for the teacher-school match quality which carries a substantial portion of the explanatory power of teacher quality to students' performance as shown in Jackson (2013).[9]

The paper is structured in seven sections. The next section briefly provides background information on education system and teachers' deployment and transfer in Senegal, and section 3 presents the data and some descriptive statistics. In section 4, we present the methodology before presenting the results in section 5 which are further discussed in section 6. Section 7 concludes.

2 Primary education and teachers' allocation in Senegal

2.1 An overview of primary education in Senegal

Ensuring access to quality education has always been a major public policy in Senegal since the country gained independence in 1960. Education is compulsory for all children between the ages of

[9] We however show in the results section that even when discounting for the teacher-school match quality effect in the most conservative manner, our preferred simulation 12 yields substantial effect on students' performance.

6 and 16, and schooling is free of charge in public education institutions, making the education sector accounting for a large fraction of the country's budget (Dienes, 2022). However, the average Senegalese child will only reach 42% of their full education and potential, and Senegal, much like many other African countries, is facing a learning crisis (UNESCO IICBA, 2024). The education system follows a 6-4-3 model, with six years for primary school, four years for lower secondary (middle) school, and three years for upper secondary (high) school, each level ending with a national examination. Senegal participates in learning assessments, including PASEC, Jàngandoo, and others, such as the PISA-D (Program for International Student Assessment for Development). These assessments keep stock of the current education system and highlight gaps that need to be addressed. They therefore help improving teaching and learning outcomes which is at the core of Senegal governments' educational priorities and goals as outlined in the PAQUET-EF (*Programme d'Amélioration de la Qualité, de l'Equité et de la Transparence*) 2018-2030. Children living in the rural areas of Senegal are often disadvantaged in terms of access and ability to complete schooling, and the uneven distribution of educational resources across regions explains significantly higher performances of students in urban areas observed across several learning assessments (Dienes, 2022). From data collected at the Senegalese Ministry of education, it appears that the large majority (about 82% in 2018-2022) of primary school students attend public school in Senegal. From 2014 to 2022, the gross enrollment rate has remained stable, at around 18% for preschool and 87% for the primary level. It decreased from 60% to 53% over the same period at the middle school level, while remaining below 35% during the same period at the high school level. These indicators show the significant efforts that still need to be made by the Senegalese government to progress towards achieving SDG4 by 2030.

2.2 Teachers' deployment and transfer

The recruitment, training, and deployment of teachers is centralized in the public sector. Candidates for primary school teacher positions must have completed upper secondary school and are required to take competitive examinations which are organized depending on the needs of the education system (Dienes, 2022). The selected candidates go through a 9-month training program after which they are assigned to schools by the Ministry of Education. Teachers are asked to express their preferences in terms of region of posting in the process. Following their initial appointment, teachers may change schools for several reasons. In Senegal, these movements are done based on guidelines and procedures which are detailed in the "*Guide pratique du mouvement des personnels enseignants*". This document which encompasses primary, secondary, and vocational education, includes forms to be filled by teachers requesting a transfer, a description of the MIRADOR which is Senegal's data-driven and ICT-based application to manage its teaching workforce, and the conditions to be eligible for a transfer and for supervision positions (e.g., principals). The last revision of the guidelines happened in 2021 following an evaluation and extensive consultations with the various stakeholders. Teachers transfer and appointment to supervision positions are based on years of experience in the current grade, gender, marital status, number of children and evaluation scores. The teacher allocations resulting from MIRADOR are only provisional. They are examined by a committee and can be modified before teachers are notified.

3 Data and descriptive statistics

3.1 Data and sample size

The paper exploits the PASEC2019 survey data for Senegal. PASEC surveys are standardized surveys that assess the education systems of candidate countries based on a large amount of detailed information collected about students, teachers, principals, classrooms, and schools' environment. The sample is nationally representative and based on a stratified three-stage design. Schools are selected in the initial stage based on the most recent sampling frame. Within each selected school, one classroom is chosen at the end of primary education (grade 5 or 6) and optionally at the beginning (grade 2 or 3) using a simple random procedure during data collection. Finally, from the selected primary classrooms and subject to class size constraints, 16 students are randomly chosen from the starting grade classrooms, and 25 students are selected from the ending grade classrooms. The PASEC2019 survey took place between April and May 2019 and included an assessment of all teachers in the selected schools on the knowledge and skills dimensions. This consisted of paper-and-pencil tests in multiple-choice format, covering both subject knowledge and teaching skills in reading comprehension and math. The early primary tests were administered to students in the 2nd grade of primary school and the late primary tests mainly assessed the knowledge and skills in reading and math needed by 6th grade students to pursue quality secondary or vocational education.

This study is based on information collected at the late primary students and teachers' levels, in addition to general information on schools and school principals. Indeed, while data is also available for second-grade students, more than two thirds of the second-grade sample have missing information on at least one of the variables required for our analysis.[10]

Our analytical sample comprises 1,374 students for which information was available on the 113 variables included in our predictive analysis. For the purposes of this study, students' test scores (five

[10] See Appendix Table 1 for the list of covariables considered in this work.

in reading and five in math) were transformed into a summary aggregate test score using the generalized least-squares weighting procedure developed in Anderson (2008).[11] There are some modest differences between the two samples, with students in the analytical sample being slightly more proficient in reading than those in the initial sample. Moreover, teachers in the analytical sample are less likely to have completed college, but the two groups have similar average scores. Also, school principals are more likely to have a university degree but less likely to be females in the study sample.[12] In total, out of 113 conditioning variables used in our predictive model, the study sample differs from the initial one with respect to only one variable (teacher's academic level), which is reassuring regarding the generalization of our results to the initial sample.

3.2 Descriptive statistics

More than a half (56%) of the students are girls, and 65% live with their two parents. Most went to kindergarten (83%) prior to starting primary school, and close to six out of 10 have already repeated a grade. Less than half of them (42%) take breakfast every school day and 13% suffer from hunger at school. About a third of them are required to do household chores on school days. Nearly all of them have a reading book at school (97%) and a math book at school (97%), but only half (50%) have books at home. Their age range is between 10 and 17 with an average of 12 years.

Only 13% of the teachers in the sample are female. Most teachers have a tertiary education (62%) and 77% earned the teaching qualification certificate (*Certificat d'Aptitude Professionnelle*). The majority (68%) is on a permanent contract as public servants, whereas 29% are involved in secondary activities to complement their monthly salary. Professional training for teachers during their career seems to be frequent in Senegal as 92% have attended at least one in the sample. Sixth grade teachers who sat for the PASEC2019 testing have 11 years of experience on average and 16% oversee multigrade classrooms. They have between 9 and 65 students with an average class size of 33 students. The schools within which these classrooms are located are all headed by male principals and predominantly in rural areas (77%). These schools are accessible throughout the academic year

[11] Compared to traditional approaches like principal component analysis, this procedure has the advantage of assigning greater weights to less correlated variables and smaller weights to more correlated ones, thereby maximizing the amount of information extracted from the data. Not only the use of a summary index is widespread in educational research, including in Senegal (e.g. Carneiro et al., 2020), but it also has the main advantage, in our predictive statistical task, of providing a view on the relation of teacher allocation to a global measure of educational achievement. Nonetheless, in a robustness check, students' outcomes were computed using simple averages of the plausible values in reading, math, and for the aggregate score. Our results remain the same (see Appendix Table 5).

[12] We consider five categories: students' test scores, students' and their families' variables, teachers' test scores, teachers' and classrooms' variables, and principals' and schools' variables. Given that the comparison entails testing many hypotheses, we correct the p-values following Romano and Wolf (2016) with a family-wise error rate of 5%.

(95%) and receive at least one inspection visit annually (82%). Most schools implement automatic grade promotion (85%) and offer tutoring hours to support students (87%). However, only a few have an annual operating budget (17%) or a school canteen (13%). Additional descriptive statistics can be found in Appendix Table 2.

4 Methodology

We describe the methodology in three sequential parts: model selection, description of the simulations, and prediction of learning outcomes under each simulation.

4.1 Model selection

Predictive research in contemporary studies prominently revolves around machine learning techniques. This study aligns with the current trend of examining the predictive efficacy of several machine learning algorithms when using machine learning techniques for predictive or simulation studies. First, we tested the predictive efficacy of the following 10 models: Ordinary Least Squares (OLS), Least Absolute Shrinkage and Selection Operator (LASSO) with Akaike Information Criterion (AIC), LASSO with Bayesian Information Criterion (BIC), LASSO with Cross-Validation (CV), Ridge Regression (RR) with CV, Elastic Net Regression (ENR) with CV, Random Forests (RF), Gradient Boosting (GB), Support Vector Machine (SVM), and Linear Support Vector Machine (Linear SVM). We then implemented the stacking approach introduced by Wolpert (1992) to combine the predictions from all these models into a single prediction, the objective being to enhance their individual performances.

In addition to Wolpert (1992)'s stacking approach, we also considered other averaging methods, but adopted the weighted average least squares (WALS) of De Luca et al. (2023) for computational reasons.[13] The model selection procedure is therefore based on all 10 individual machine learners above, a meta-machine learner stacking these individual machine learning algorithms, and the WALS estimator.

[13] We also considered several other averaging techniques, such as multi-model inference using information criteria, Mallows model averaging, and Jackknife model averaging. However, these methods come with much higher computational burdens, especially when dealing with numerous variables, as the model space consists of 2^k models where k is the number of candidate variables. Beyond averaging techniques, we also explored generalized additive models, which offer flexibility and the ability to model non-linear relationships. However, these models introduce additional complexity, particularly in terms of computational demands and hyperparameter tuning. Key hyperparameters, such as the smoothing parameter, choice of basis functions, and the number of knots, require careful adjustment, which can be computationally intensive. Given the study's focus on maximizing predictive accuracy while maintaining computational efficiency, we decided to prioritize models that are more straightforward to implement and seamlessly integrate into ensemble methods like stacking and WALS. This approach ensures that the models remain computationally feasible and can be effectively combined without introducing unnecessary complexity.

Table 1: Root-Mean Squared Error of the machine learning algorithms

Machine learning algorithm	Reading	Math	Aggregate score
OLS	0.931	0.940	0.923
LASSO with AIC	0.903	0.912	0.895
LASSO with BIC	0.895	0.899	0.885
LASSO with CV	0.905	0.914	0.897
RR with CV	0.931	0.940	0.923
ENR with CV	0.904	0.914	0.896
RF	0.910	0.923	0.896
GB	0.909	0.920	0.897
SVM	0.940	0.941	0.928
Linear SVM	0.945	0.979	0.974
Wolpert's stacking of all previous learners	0.909	0.919	0.896
WALS	0.563	0.518	0.536

Notes: Authors calculations based on PASEC2019 data for Senegal

To assess the predictive efficacy of the different models, our sample is split into a training sample (70% of the original sample) and a testing sample (30% of the original sample)[14]. Table 1 shows the performance (estimated on the testing sample) of each model (learner) based on the root-mean squared error (RMSE) criterion. The RMSE is lower for the WALS which is hence adopted to predict student scores.

Suppose y (n x 1) is our vector of observations on test scores, $X = (X_1, X_2)$ with X_1 (n x k_1) and X_2 (n x k_2) are matrices of non-random regressors (our conditioning variables), β_1 and β_2 are unknown parameter vectors, and ε is a vector of random disturbances. Following the philosophy of De Luca et al. (2023), we can write:

$$y = X\beta + \varepsilon = X_1\beta_1 + X_2\beta_2 + \varepsilon \tag{1}$$

The k_1 columns of X_1 contain the 'focus regressors' which we want in the model on theoretical or other grounds ($k_1=1$ in this case), while the k_2 columns of X_2 contain the 'auxiliary regressors' of which we are less certain. These auxiliary regressors could be controls that are added to avoid omitted-variable bias or transformations and interactions of the set of original regressors. It is assumed that $k_1 \geq 1$, $k_2 \geq 0$ and X has full column-rank $k = k_1 + k_2 \leq n$. The disturbance vector ε has zero mean and a positive definite variance matrix, diagonal but not necessarily equal to $\sigma^2 I_n$. In our case, k_1=1 and k_2=113, suggesting that only the intercept is the primary focus regressor. This also means that we are uncertain about the role of our 113 auxiliary variables. There are $2^{k2} = 2^{113}$ possible models that contain the intercept (our only focus regressor) and a (possibly empty) subset of the auxiliary regressors. While this number of models is exceptionally high, it is worth noting that the

[14] Our model selection is robust to the partitions considered, with the WALS method consistently performing the best across the 60/40, 75/25 and 80/20 partitions.

WALS procedure involves a preliminary orthogonal transformation of the auxiliary regressors, which significantly reduces the computational burden of the model averaging estimator.

If $\hat{\beta}_{1j}$ and $\hat{\beta}_{2j}$ are the least squares estimators of β_1 and β_2 in model j and δ_j are nonnegative data-dependent model weights that add up to one, then the WALS averaging estimators take the following form:

$$\hat{\beta}_1 = \sum_{j=1}^{2^{k_2}} \delta_j \, \hat{\beta}_{1j} \tag{2}$$

$$\hat{\beta}_2 = \sum_{j=1}^{2^{k_2}} \delta_j \, \hat{\beta}_{2j} \tag{3}$$

The WALS approach is a frequentist model averaging approach that incorporates a Bayesian perspective: the intuition behind it is to estimate the parameters of each model using linear regression, and then average these parameters using weights based on posterior model probabilities, in a Bayesian sense.

4.2 Simulations

This paper considers six types of simulations, based on randomness, students' needs, teachers' skills, and teachers' length of service. Each type is operationalized at both the national and regional levels, resulting in a total of 12 distinct simulations. During the reshuffling process, teachers' characteristics are collectively transferred to new schools according to the different simulations. This involves relocating all teacher attributes based on the specific reshuffling conditions outlined below.

- *Simulation 1: Random shuffling of teachers at the national level.*

We randomly assign teachers to classrooms, disregarding deterministic factors that could influence student performance. The idea here is to see how the existing allocation mechanism − which is based on a priori information on schools' needs and teachers' preferences compares with a purely random assignment which offers equal opportunity for classrooms to get high-quality teachers. We posit that an allocation mechanism using a priori information (the existing system) will always be more effective than a random assignment, assuming that the current system is well-aligned with the needs of the education system.

- *Simulation 2: Random shuffling of teachers at the regional level.*

Simulation 2 is the regional version of simulation 1. The random shuffling is performed within each region instead of at national level. The regional option reduces the transaction costs associated with moving to another region.

- *Simulation 3: Teachers with the best-performing students replace those with the least-performing students at the national level.*

In this simulation, classrooms are ranked based on the average score of the students and teachers are ranked accordingly. Teachers are then shuffled around so that teachers whose students had the highest average score are now allocated to classrooms where students had the lowest average score. The underlying assumptions of this simulation are the following: (i) teachers with high-performing classrooms are of higher quality on average and (ii) reassigning these teachers to low-performing classrooms matches teacher quality with students' needs and is similar to getting 'average student' being taught by an 'average quality teacher'. This simulation is therefore primarily expected to improve equity.

- *Simulation 4: Teachers with the best-performing students replace those with the least-performing students at the regional level.*

This is the regional version of simulation 3.

- *Simulation 5: Teachers with the highest skill levels rotate with those with the lowest skill levels nationally.*

The rationale of this simulation lies into a political economy dimension of the assignment of high-quality teachers. As found by the Research on Improving Systems of Education (RISE) program, education systems in many SSA countries are aligned for different purposes, except learning; and one of this purpose might be securing electoral support by allocating best teachers to localities that are more favourable to the government in place. Although we have no evidence of such practices in the case of Senegal, we nevertheless assume that the existing distribution of quality teachers across school may partly incorporate such a strategy. Hence, we implement the exact opposite in this simulation by ranking teachers based on their aggregate score, say from 1^{st} to n^{th}, and then rotate teacher with rank p with teacher with rank n-p+1. Outcomes are less predictable than in simulations 3 and 4.

- *Simulation 6: Teachers with the highest skill levels rotate with those with the lowest skill levels regionally.*

This is the regional version of simulation 5.

- *Simulation 7: Teachers with the highest skill levels are allocated to low-performing classrooms and vice-versa at the national level.*

This approach aims to allocate the best teachers to those with the greatest needs. This strategy is expected to improve the performance of low-performing classrooms and potentially enhance overall student performance across the system. However, there may be trade-offs, such as increased inequalities, as individuals in the middle of the learning outcomes distribution (with fair performance) may have benefited more under the status quo and are now deprived of access to high-performing teachers. In practice, teachers are ranked from 1 to n based on their aggregate score and classrooms are ranked from 1 to n based on student average score. A teacher with rank p is matched with classroom with rank n-p+1.

- *Simulation 8: Teachers with the highest skill levels are allocated to low-performing classrooms and vice-versa at the regional level.*

Simulation 8 is simulation 7 implemented within each region instead of at the national level.

- *Simulation 9: More experienced teachers rotate with the less experienced ones at the national level.*

This approach operates similarly to simulation 5, with the allocation factor now being the years of experience. The same rationale applies, and the execution is similar.

- *Simulation 10: More experienced teachers rotate with the less experienced ones at the regional level.*

This is the regional version of simulation 9.

- *Simulation 11: More experienced teachers are allocated to low-performing classrooms and vice-versa at the national level.*

This setting is similar to simulation 7, but the allocation is based on the number of years of experience. The same rationale and analysis are applicable. However, it is important to note that obtaining information about years of experience is more cost-effective than assessing teacher performance through standardized tests, given that teacher's years of experience is typically available in the databases of education systems. Therefore, in terms of implementation cost and operational efficiency, an allocation based on years of experience may be preferable.

- *Simulation 12: More experienced teachers are allocated to low-performing classrooms and vice-versa at the regional level.*

This is the regional version of simulation 11.

4.3 Prediction

Before reshuffling, we estimate baseline coefficients for each test score (reading, math, and aggregate score) using the WALS approach. These coefficients capture the relationships between test scores and conditioning variables in the education system at the time of data collection and are interpreted as structural parameters. After the reshuffling process of each simulation, these coefficients are used to estimate new student scores as a linear combination of all variables in the model.

5 Results

5.1 Main findings

We measure the effects of teacher allocation on quality, defined as the mean of students' test scores, and on education equity, captured by the standard deviation (SD) of students' test scores distribution. The mean and SD resulting from each simulation are compared to the corresponding baseline values. We further assess how other distributional statistics such as percentiles vary across the different simulations.

The results of the simulations are presented in Table 2 below. Simulations 1 and 2 entail a random reshuffling of teachers at regional and national level, respectively. The random reshuffling is replicated 5,000 times to draw the distribution of students' test scores.[15] Empirical 95% confidence intervals are estimated to gauge significance of these results are reported in Appendix Table 3. The results show that on average, a random allocation improves the mean of student's aggregate score by 0.065 unit when conducted at the national level and by 0.079 unit when conducted at the regional level, corresponding to around 0.904 baseline SD. The SD more than doubles in both cases: it increases from 0.691 to 1.730 in simulation 1 and to 1.703 in simulation 2 (see Cols. 1 and 2, Table 2).

The second group of simulations is based on students' performances: teachers with the highest performing students replace those with the lowest performing students and vice-versa, at the national level (simulation 3) and regional level (simulation 4). Simulation 3 improves the mean of students' aggregate score by 0.110 unit but reduces equity, as it also increases the SD (from 0.691 to 1.619). Similar results are obtained with simulation 4: an improvement by 0.102 unit of the mean of students' aggregate score together with an increase of the SD by 0.854. The effects of simulations 3 and 4 are equivalent to around 15% of the baseline SD.

[15] Our conclusions remain the same when the number of replications is increased from 5,000 to 10,000 as shown in Appendix Table 4.

Table 2: Effects of the simulations on the distribution of student's aggregate score – 5,000 replications

Statistics	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		Random shuffling at national level	Random shuffling at regional level	Teachers with the best performing students replace teachers with the least performing students at the national level.	Teachers with the best performing students replace teachers with the least performing students at the regional level	High-skill teachers rotate with the ones with lower skills at the national level.	High-skill teachers rotate with the ones with lower skills at the regional level.	High-skill teachers are allocated to low-performing classrooms and vice-versa at the national level.	High-skill teachers are allocated to low-performing classrooms and vice-versa at the regional level.	More experienced teachers rotate with the less experienced ones at the national level.	More experienced teachers rotate with the less experienced ones at the regional level.	Most experienced teachers are allocated to low-performing classrooms and vice-versa at the national level.	Most experienced teachers are allocated to low-performing classrooms and vice-versa at the regional level.
Min	**-2.648**	-4.673	-4.501	-4.286	-5.308	-4.042	-3.977	-4.750	-3.998	-5.228	-3.998	-4.394	-5.308
Max	**1.859**	4.546	4.297	4.109	5.571	4.273	4.534	4.165	4.166	4.878	4.576	4.192	4.576
Mean	**0.000**	0.065	0.079	0.110	0.102	0.072	0.128	0.053	0.073	0.098	0.075	0.049	0.149
p10	**-0.938**	-2.160	-2.146	-1.873	-1.786	-2.285	-1.971	-2.076	-2.185	-2.198	-2.151	-2.105	-2.152
p25	**-0.400**	-1.093	-1.065	-1.064	-0.906	-1.452	-0.840	-1.144	-1.066	-1.022	-1.139	-1.209	-0.821
p50	**0.089**	0.057	0.099	0.150	0.175	0.209	0.044	-0.003	0.053	-0.042	0.055	-0.067	0.311
p75	**0.515**	1.227	1.268	1.200	1.045	1.487	1.147	1.347	1.135	1.456	1.166	1.248	1.267
p90	**0.771**	2.306	2.281	2.020	1.809	2.522	2.221	2.382	2.511	2.344	2.258	2.514	2.223
SD	**0.691**	1.730	1.703	1.619	1.545	1.781	1.548	1.709	1.670	1.867	1.699	1.787	1.679
Variation of mean score (a)	-	0.065	0.079	0.110	0.102	0.072	0.128	0.053	0.073	0.098	0.075	0.049	0.149
Variation of the SD (b)	-	1.040	1.012	0.928	0.854	1.090	0.858	1.018	0.980	1.176	1.009	1.096	0.988
(b)/(a)	**-**	**16.1**	**12.8**	**8.4**	**8.3**	**15.2**	**6.7**	**19.2**	**13.4**	**12.0**	**13.4**	**22.5**	**6.6**

Notes: Authors calculations based on PASEC2019 data for Senegal.

p10, p25, p50, p75 and p90 are the 10^{th}, 25^{th}, 50^{th} (median), 75^{th} and 90^{th} percentiles, respectively.

The third set of simulations (simulations 5 to 8) draws upon teachers' knowledge and skills. In the 5th and 6th simulations, teachers are permuted based on their skills (teachers with higher test scores replace teachers with lower scores, and vice-versa) at the national and regional levels, respectively. Simulation 5 improves the mean score by 0.072 unit and decreases equity with the SD moving from 0.691 to 1.781, whereas the permutation within regions (simulation 6) increases the mean score by 0.128 with a less deteriorating effect on equity (the SD increases to 1.548). In simulations 7 and 8, we reallocate the teachers with higher skills to classrooms with lower average students' scores, at national and regional levels, respectively. As a result, the mean students' aggregate score improves by 0.053 unit and 0.073 unit, respectively. Like the previous simulations, these improvements in terms of quality are at the cost of a substantial increase in inequality: the SD is 1.709 in simulation 7 and 1.670 in simulation 8.

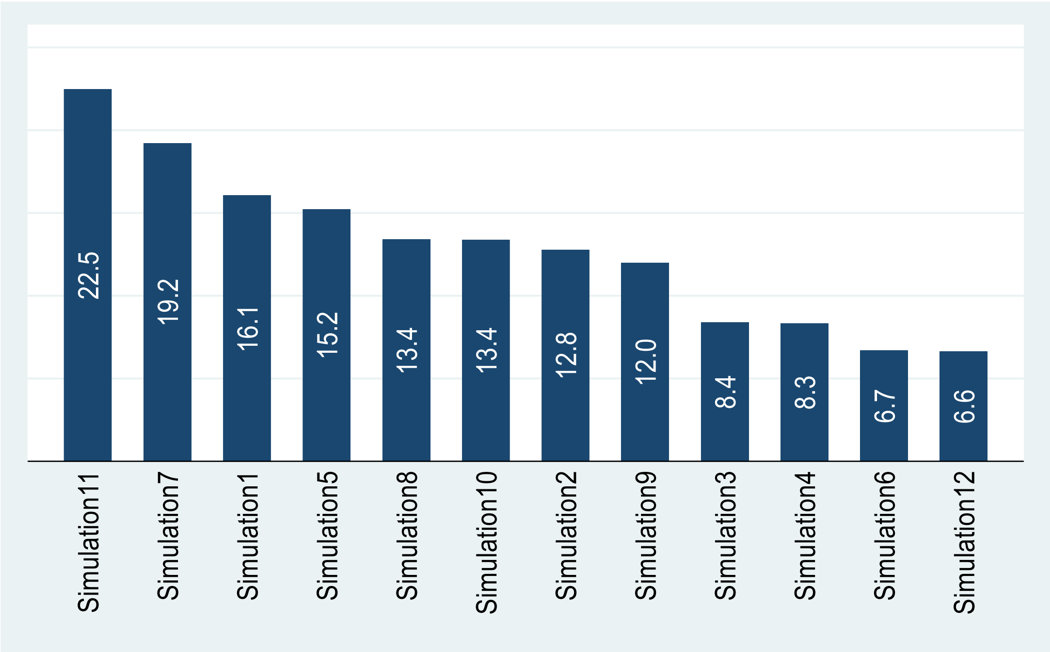
Teachers' years of experience is at the core of the last set of simulations (9 to 12). The most experienced teachers rotate with the least experienced ones at national level in simulation 9 and at regional level in simulation 10. Simulations 9 and 10 increase the mean of the aggregate score by 0.098 unit and 0.075 unit, respectively. They also negatively affect equity as they result in an increase of the SD to 1.867 for simulation 9 and 1.699 for simulation 10.

Simulations 11 and 12 consist of assigning the more experienced teachers to the classrooms with lower average students' scores and vice-versa, at national and regional levels, respectively. The mean aggregate score is increased by 0.049 in simulation 11 (lowest effect on quality across all simulations) and by 0.149 in simulation 12 (highest effect on quality across all simulations) whereas the SD is raised by 1.096 and 0.988, respectively (Cols. 11 and 12, Table 2).

To allow a meaningful comparison across the 12 simulations, we divide the effect on equity by the effect on quality to obtain a ratio which is interpreted as the equity cost per unit of quality improvement.[16] These ratios are reported at the bottom of Table 2. Figure 1 presents a ranking of all 12 simulations based on this ratio for the aggregate test score. Similar graphs are provided in Appendix Figure 1 and Appendix Figure 2 for the reading and math test scores, respectively.

[16] The equity cost per unit of quality improvement is relevant only when the quality effect is strictly positive. A lower ratio indicates that for every unit of improvement in quality, there is a relatively smaller impact on equity, suggesting that the strategy is more balanced and potentially more desirable. A higher ratio on the other hand would suggest that the quality improvements come at a significant equity cost, meaning that while average student performance might improve, it could be at the expense of increasing disparities between students, which would be less desirable.

Figure 1: Equity cost per unit of quality improvement, Aggregate score



Note: Simulations details are provided in sub-section 4.2 of this paper.

Simulation 12 (transferring the more experienced teachers to low performing classrooms and vice-versa at the regional level) and simulation 6 (teachers with higher skills are permuted teachers with lower skills at the regional level) have the lowest ratios (6.6 and 6.7, respectively). They are followed by simulation 4 (teachers with high performing students are permuted with teachers with low performing students at the regional level) and simulation 3 (teachers with high performing students are permuted with teachers with low performing students at national level) with ratios of 8.3 and 8.4, respectively. The highest ratios are obtained for simulation 7 (19.2) and simulation 11 (22.5) which are the corresponding of simulations 6 and 12 at the national level. More generally, the average ratio is lower for simulations at the regional level compared to simulations at the national level (10.2 against 15.6), suggesting that regional level teachers transfer schemes might be more effective than the national level ones in reconciling quality improvement with inequality reduction in primary education system in Senegal. Also, the average ratio is lowest for simulations based on students' performances (average ratio of 8.4 for simulations 3 and 4) and highest for simulation based on random allocation (average ratio of 14.4 for simulations 1 and 2).

Overall, all 12 simulations have a positive effect on quality via an increase of the mean of students' aggregate score (from 0.049 in simulation 11 to 0.149 in simulation 12), but they also negatively affect equity given that they increase the SD of the aggregate score (from 0.854 in simulation 4 to 1.176 in simulation 9). When discounting for the teacher-school match quality effect (assumed to be

0 and taking away a quarter of teacher quality effect[17]), the increase of the mean of the aggregate score is reduced and ranges between 0.037 and 0.11, corresponding to 0.05 SD and 0.16 SD, respectively. Although modest in absolute terms (<0.2 SD), the discounted quality effect of simulation 12 (which corresponds to 0.16 SD) is larger than the effect of school grants on students' performance in Senegal (0.126 SD for 3rd graders and close to zero for 5th graders in Carneiro et al., 2020). The allocation of more experienced teachers to low-performing classrooms and vice-versa at the regional level in Senegal is also much more effective than permanently doubling the base pay of teachers which led to no improvements in student learning outcomes in Indonesia (De Ree et al., 2018), and produces effects that are similar to that of a daily monitoring of teachers' attendance using cameras in India (estimated at a 0.17 SD improvement in students' math and Hindi test scores after 30 months by Duflo, Hanna, & Ryan, 2012). Finally, the positive effects on quality paired with the negative effects on equity observed across all simulations suggest the existence of a trade-off between quality and equity in primary education in Senegal.

5.2 Heterogeneity

We explore the heterogeneity of quality and equity effects with respect to topic (reading/math), gender (boys/girls), residence area (urban/rural) and socioeconomic background (poor/rich). The Appendix Table 6 shows that the quality effect of teachers reshuffling is positive on students' scores across all 12 simulations both in reading and in math. The effect is larger for reading scores than for math scores in all but simulation 11, which has the highest equity cost per unit of quality improvement. The effects on equity are also negative (meaning an increase of the SD) in both subjects, but with more pronounced effects in reading. The equity cost for math is highest in simulation 7 (high-skill teachers are allocated to low-performing classrooms at the national level; ratio of 22.6) and lowest in simulation 12 (more experienced teachers are allocated to low-performing classrooms at the regional level; 6.6). It is highest in simulation 11 (more experienced teachers are allocated to low-performing classrooms at the national level; 28.2) and lowest in simulation 6 (high-skill teachers rotate with low-skill ones at the regional level; 6.6) for reading.

All 12 simulations negatively impact students at the bottom of the distribution of scores as shown in Appendix Table 10. For instance, the first decile (p10) decreases by 0.849 in simulation 4 and by 1.348 in simulation 5. Similarly, the first quartile (p25) falls by 0.422 in simulation 12 and 1.053 in

[17] We discount the teachers' reallocation quality effect by a quarter based on Jackson (2013)'s finding that match quality explains away a quarter of and has two-thirds the explanatory power of teacher quality. In doing so, we assume the worst-case simulation of zero teacher-school match across all simulations, which is unlikely given that some reallocations are done at the regional level.

simulation 5. The median is also reduced in 7 simulations out of the 12. It is noted that simulation 12 has the strongest positive effect on the median. Conversely, the top students are better-off in all simulations: the top quartile (p75) increases by 0.530 in simulation 4 and by 0.972 in simulation 5, while the top decile (p90) is raised by 1.038 and 1.751 in simulations 4 and 5, respectively. Looking at the simulations with highest equity cost (simulations 7 and 11), the first decile reduces from -0.938 at baseline to -2.076 in simulation 7 and to -2.105 in simulation 11, whereas the top decile is three times higher (from 0.771 to 2.382 in simulation 7 and to 2.514 in simulation 11).

With respect to gender (see Appendix Table 7), boys are better-off than girls in terms of quality effect in all but simulations 7 and 9, and the negative equity effect is lower for boys in all simulations except in simulations 9 and 12. The quality effect for boys is more than 3 times higher than that of girls in simulations 3, 4, 6 and 10 and the equity cost ratio is always lower for boys except for simulations 7 and 9 in which the quality effect is higher for girls. Interestingly, only simulation 12 yields balanced gender effects both in terms of quality, equity and equity cost ratio.

Considering residence area in the Appendix Table 8, students living in rural areas benefit most from simulations 1, 2, 3, 7 and 11 in which they enjoy higher quality effects and lower negative equity effects compared to their counterparts of urban areas. Conversely, only simulation 6 benefits students in urban areas more, both in terms of quality and equity. In simulations 4, 8, 9, 10 and 12, the quality effect is larger for urban students, but with a more pronounced negative equity effect compared to students in rural areas. Quality and equity effects are similar for students in urban and rural areas in simulation 5. Simulations 11 and 6 have the lowest equity cost ratio for students in rural areas (6.5) and students in urban schools (2.2), respectively. Simulation 11, which has the overall highest equity cost ratio, only benefits students in rural areas and substantially negatively impacts students in urban areas while simulation 12, with the overall lowest equity cost ratio, benefits more students in urban areas.

Finally, results in Appendix Table 9 show that a positive quality effect is observed for students from poorer families only in simulations 9 and 10, contrary to students from richer families, for whom the quality effect is positive and sizeable across all simulations.[18] Only simulation 9 produces relatively balanced effects for both groups in terms of quality and equity. Simulation 12 decreases equity in a similar magnitude for both students from poorer and richer families, but no quality improvement is observed in the first group whereas the quality improvement is the highest for second group.

[18] The median of household's wealth index is used as poverty line.

6 Discussion

This study has demonstrated that transferring teachers based on randomness, students' needs, teachers' skills, and teachers' length of service has a positive effect on quality of education in Senegal but a negative effect on equity. To understand how the different reshuffling approaches affect students' scores distribution, we first examine transition matrices to see students' movements across deciles in the different simulations, focusing on those with the lowest and the highest equity cost, i.e., simulations 12 and 11, respectively. Close to four out of 10 (38%) students improve their decile in simulation 12, with the second decile at baseline recording the highest share of students moving to higher deciles (66%). Although the quality effect in simulation 11 is one third of that of simulation 12 (0.049 against 0.149), the percentage of students improving their deciles in the former is higher than in the latter (44% as opposed to 38%). Compared to the baseline situation, the most important decile upgrades in simulation 11 occurred in the first three deciles with percentages of 82 in the 1st decile, 68 in the 2nd decile and 57 in the 3rd decile, while the corresponding figures for simulation 12 are 66%, 66% and 54%. These figures combined with lower effect on quality and higher equity cost of simulation 11 evidence that although students might be transitioning more to a higher decile in simulation 11, their improvements in terms of increased aggregate score are lower, particularly in the first deciles. More generally, these transitions and the heterogeneous effects across deciles show that the simulations results are aggregates of deteriorations of students' scores in lower deciles and a relatively strong increases of students' scores in top deciles.

Next, we look at how the reshufflings affect some key teacher-level variables across low, average and high performing classrooms in the simulations (see Appendix Table 11). At baseline, there are no significant differences between these three categories of classrooms with respect to teacher's score in reading, score in math, aggregate score, experience and absenteeism. Only a slight difference is observed regarding teacher's gender with the proportion of female teachers being lower in low and average performing classrooms compared to that of high performing classrooms. As expected, simulations 11 and 12 result into a significantly higher average years of experience for teachers assigned to low and average performing classrooms, with more pronounced differences in simulation 11. Teacher's absenteeism remains the same after simulations 11 and 12 as compared to the baseline situation, with no significant differences between the three categories of classrooms. Simulation 12 seems to reduce the quality of teachers assigned to low performing classrooms (significantly lower teacher's total score compared to the other two categories and with respect to baseline situation), mainly driven by lower teacher's score in math. Lastly, the teacher gender differences between low and average, and high performing classrooms at baseline are widened with simulation 11, whereas the proportion of female teachers is similar in low and high performing classrooms after simulation 12, yet significantly higher than in average classrooms. Altogether, this confirms that teacher's quality (captured by the aggregate test score) and experience are key factors to improving education quality and equity.

Some results of the simulations might appear counter-intuitive, particularly that of the assignment of high-quality teachers to low-performing classrooms (simulations 7 and 8) and the assignment of the most experienced teachers to low-performing classrooms (simulations 11 and 12), as they also deteriorate the situation of less performing students. Contrary to some previous studies (e.g., Araujo et al., 2016), these simulations results show that high-skilled or more experienced teachers may not automatically improve disadvantaged students learning outcomes the most and reflect perhaps the need to account more for students' level in the teaching.

Simulations based on teachers' years of experience (simulations 9 to 12) yield results that are close to those of simulation based on teachers' skills (simulations 5 to 8), which is suggestive of a positive correlation between teacher's length of service and their skills. In fact, the PASEC2019 report finds a "long service bonus" in teachers' skills both in reading comprehension and in math, whereby teachers with a longer service record showing greater subject knowledge and skills than novices. Finally, the differences in the results of simulations at the regional level and their exact counterparts at the national level (average quality effect of 0.101 against 0.074 for an average equity cost of 10.2 against 15.6) are likely explained by larger variance within regions in terms of teachers' quality and students' aggregate score as compared to between regions differences.[19]

7 Conclusion

The main objective of this paper was to assess whether better outcomes in terms of education quality and equity can be achieved through a better allocation of the existing stock of teaching capacities in primary education in Senegal, with the ambition to draw some lessons that can help tackle issues of low quality of education, shortage and misallocation of (qualified) teachers, and efficiency of education public expenditures which are common to many countries in SSA. To do so, we use machine-learning techniques with the assumption that a data-driven and ICT-based allocation of teachers will help circumvent potential biases and flaws of existing allocation and transfer mechanisms which may involve several transactions and arbitrages. We tested 12 simulations based

[19] A one-way analysis of the variances shows that more than 75% of the total variance in students' scores and more than 90% of the total variance in teachers' quality come from within regions.

on randomness, students' needs, teachers' skills, and teachers' length of service, and assess their effect on education quality and equity for late primary school students.

Our results show that students' performance improves across all 12 simulations tested, but the standard deviation of performance also increases, indicating a reduction in equity. Additionally, the simulations have varying effects: they tend to negatively impact the learning outcomes of students at the bottom of the score distribution while benefiting those at the top. A comparison across the 12 simulations suggests that assigning more experienced teachers to low-performing classrooms at the regional level could be a potential solution to balance the necessary improvement in education quality with the goal of equity in Senegal's education system. Even after accounting for the fact that this proposed reallocation does not consider teachers' preferences, its impact on quality remains substantial and compares favorably, if not better, with some more costly interventions (e.g., school grants in Senegal, doubling teachers' base pay in Indonesia, or daily monitoring of teachers' attendance using cameras in India).

This reflection is predictive in nature and assumes that the underlying existing structures and relationships between variables in the data will remain as such, thereby disregarding the behavioural responses that may arise in each simulation. Moreover, the introduction of ICT tools to guide teacher transfers does not automatically annihilate all corruption and patronage or rent-seeking practices. The impact rather depends on the matching between ICT tools and the local context, including support for and skills in using technology (Adam & Fazekas, 2021), and combines problems of technology diffusion, information economics, and behavioural economics (Mullainathan & Spiess, 2017). In the specific case of Senegal, teacher allocation and transfer are done based on guidelines and procedures which are publicly available and by using data-driven and ICT-based application (MIRADOR). Both teachers' years of experience and students' performance are public and readily available information, which should facilitate the assignment of more experienced teachers to low performing classrooms at the regional level as recommended by our findings. In this light, Senegalese authorities might consider adopting a more pragmatic approach to teacher transfers, rather than mainly attending to transfer requests. Moreover, any interference that distorts transfers generated by MIRADOR should be exceptional, with clearly defined and transparent conditions.

References

Adam, I., & Fazekas, M. (2021). Are emerging technologies helping win the fight against corruption? A review of the state of evidence. *Information Economics and Policy, 57*, 100950.

Akbarpour, M., Kapor, A., Neilson, C., Van Dijk, W., & Zimmerman, S. (2022). Centralized school choice with unequal outside options. *Journal of Public Economics, 210*, 104644.

Anderson, M. L. (2008). Multiple inference and gender differences in the effects of early intervention: A reevaluation of the abecedarian, perry preschool, and early training projects. *Journal of the American Statistical Association*, *103*(484), 1481–1495.

Araujo, M. C., Carneiro, P., Cruz-Aguayo, Y., & Schady, N. (2016). Teacher quality and learning outcomes in kindergarten. *The Quarterly Journal of Economics, 131*(3), 1415-1453.

Alidou, S., & Koussihouede, O. (2024). Urban-rural differences in teachers' qualification and competences in primary education in Francophone Sub-Saharan Africa. *Association for the Development of Education in Africa (ADEA)*, 1–16.

Arteaga, F., Kapor, A. J., Neilson, C. A., & Zimmerman, S. D. (2022). Smart matching platforms and heterogeneous beliefs in centralized school choice. *The Quarterly Journal of Economics, 137*(3), 1791-1848.

Carneiro, P., Koussihouèdé, O., Lahire, N., Meghir, C., & Mommaerts, C. (2020). School grants and education quality: Experimental evidence from Senegal. *Economica, 87*(345), 28-51.

Chetty, R., Friedman, J. N., & Rockoff, J. E. (2014). Measuring the impacts of teachers I: Evaluating bias in teacher value-added estimates. *American Economic Review, 104*(9), 2593-2632.

De Luca, G., Magnus, J. R., & Peracchi, F. (2023). Weighted-average least squares (WALS): Confidence and prediction intervals. *Computational Economics, 61*(4), 1637-1664.

De Ree, J., Muralidharan, K., Pradhan, M., & Rogers, H. (2018). Double for nothing? Experimental evidence on an unconditional teacher salary increase in Indonesia. *The Quarterly Journal of Economics, 133*(2), 993-1039.

Dienes, S. (2022). Quality education in Senegal: Overview and opportunities for improvement.

Duflo, E., Hanna, R., & Ryan, S. P. (2012). Incentives work: Getting teachers to come to school. *American Economic Review, 102*(4), 1241-1278.

Elbahnasawy, N. G. (2021). Can e-government limit the scope of the informal economy? *World Development, 139*, 105341.

Elacqua, G., Westh Olsen, A. S., & Velez-Ferro, S. (2021). The market design approach to teacher assignment: Evidence from Ecuador (No. IDB-WP-1294). *IDB Working Paper Series*.

Elacqua, G., Gómez, L., Krussig, T., Marotta, L., Méndez, C., & Neilson, C. A. (2022). The potential of smart matching platforms in teacher assignment: The case of Ecuador (No. IDB-WP-01395). *IDB Working Paper Series*.

Haruna, E. U., & Alhassan, U. (2022). Does digitalization limit the proliferation of the shadow economy in African countries? An in-depth panel analysis. *African Development Review, 34*, S34-S62.

Jackson, C. K. (2013). Match quality, worker productivity, and worker mobility: Direct evidence from teachers. *Review of Economics and Statistics, 95*(4), 1096-1116.

Jackson, C. K. (2018). What do test scores miss? The importance of teacher effects on non–test score outcomes. *Journal of Political Economy, 126*(5), 2072-2107.

Michaelowa, K. (2001). Primary education quality in francophone Sub-Saharan Africa: Determinants of learning achievement and efficiency considerations. *World Development, 29*(10), 1699-1716.

Mulkeen, A. (2005). Teachers for rural schools: A challenge for Africa. Rome: *FAO*.

Mullainathan, S., & Spiess, J. (2017). Machine learning: An applied econometric approach. *Journal of Economic Perspectives, 31*(2), 87-106.

Muralidharan, K., Niehaus, P., & Sukhtankar, S. (2016). Building state capacity: Evidence from biometric smartcards in India. *American Economic Review, 106*(10), 2895-2929.

PASEC (2022). PASEC 2019 Quality of education system in French-speaking Sub-Saharan Africa.

Ramachandran, V., Béteille, T., Linden, T., Dey, S., & Chatterjee, P. G. (2017). Getting the right teachers into the right schools: Managing India's teacher workforce. *World Bank Publications*.

Rees-Jones, A., & Shorrer, R. (2023). Behavioral economics in education market design: A forward-looking review. *Journal of Political Economy Microeconomics, 1*(3), 557-613.

Rivkin, S. G., Hanushek, E. A., & Kain, J. F. (2005). Teachers, schools, and academic achievement. *Econometrica, 73*(2), 417-458.

Romano, J. P., & Wolf, M. (2016). Efficient computation of adjusted p-values for resampling-based stepdown multiple testing. *Statistics and Probability Letters, 113*, 38-40.

République du Sénégal. (2018). *Guide pratique du mouvement des personnels enseignants*. Ministère de l'Éducation Nationale du Sénégal.

UNESCO IICBA. (2024). *Senegal: Education Country Brief*. UNESCO's International Institute for Capacity Building in Africa.

Wolpert, D. H. (1992). Stacked generalization. *Neural Networks, 5*(2), 241-259.

Annexes

Appendix Table 1 : List of variables used for the prediction and/or used for comparing the analytical sample to the original one

Student level variables		
Student is female	Always does domestic work during the school year	Often speaks French at home
Lives with the 2 parents	Often does domestic work during the school year	Sometimes speaks French at home
Attended public kindergarten	Sometimes does domestic work during the school year	Never speaks French at home
Attended private kindergarten	Never does domestic work during the school year	Mother can read French
Attended denominational kindergarten	Always does agricultural work during the school year	Has homework given by the teacher
Attended kindergarten (any type)	Often does farm activities during the school year	Is helped with homework
Attended koranic school before primary school	Sometimes does farm activities during the school year	Reads at home
Has ever repeated a grade	Never does farm activities during the school year	Has a reading book in class
Has eyesight problems	Does small commercial activities during the school year	Has a math book in class
Has breakfast everyday	Often does small commercial activities during the school year	Has books at home
Has breakfast often	Sometimes does small commercial activities during the school year	Average aggregate score for other students in the classroom
Has breakfast sometimes	Never does small commercial activities during the school year	Household wealth index
Has never breakfast	Always does manual work/small commercial activities throughout the year	Average household wealth index of other students in the class
Is always hungry at school	Often does manual work/small commercial activities throughout the year	Age (in years)
Is often hungry at school	Sometimes does manual work/small commercial activities throughout the year	Score in reading
Is sometimes hungry at school	Never does manual work/small commercial activities	Score in math
Is never hungry at school	Always speaks French at home	Aggregate score
Teacher and classroom levels variables		
Teacher is female	Received 1 year of initial professional training	Single grade classroom
Attended primary school	Received 2 years of initial professional training	Multi grade classroom
Attended secondary school	Received more than three years of initial professional training	Class size
Attended high school	Ever attended additional professional training	Class equipment index
Attended university	Is civil servant	Score in reading
Has no professional diploma	Is a contract teacher	Score in math
Did a professional internship	Community teacher	Aggregated score (reading and math)

Has the CEAP	Receive salary on a regular basis	Score in teaching math
Has the CAP	Has a secondary activity	Score in teaching reading
Ha sthe CFEN	Years of experience	Aggregated teacher score in teaching (reading and math)
Received less than 6 months of initial professional training	Absenteeism in the last two months (# days)	
Principal and school levels variables		
Principal is female	School with multigrade classes	School provides 3 hours tutoring to students
Attended primary school	Schools with double shift	School provides 2 hours tutoring to students
Attended high school	Urban school	School provides max 1 hour tutoring to students
Attended university	Easy access to school all year	School has an annual budget
Has no professional diploma	School receives an inspection during the academic year	Has a school canteen
Did a professional internship	Meeting with parents	Number of 6^{th} grade students in the school
Has the CEAP	School teaches the official curriculum for reading	Number of teachers in the school
Has the CAP	School teaches the official curriculum for math	Number of days of strike in the school
Years of experience as principal	School applies automatic grade promotion	School infrastructure index
Years of experience as teacher (before principal position)	School does not provide tutoring to students	Community participation index
School has all 6 grades	School provides 5 hours tutoring to students	Basic infrastructures index of the city block/village
School with single grade classes	School provides 4 hours tutoring to students	

Notes: Authors, based on PASEC2019 data for Senegal

Appendix Table 2 : Descriptive statistics on selected variables

	Low performing classrooms	Average performing classrooms	High performing classrooms	All
Panel A: Students' characteristics and family background				
Student is female	0.515 (0.500)	0.576 (0.495)	0.577 (0.495)	0.559 (0.497)
Lives with the 2 parents	0.668 (0.472)	0.661 (0.474)	0.589 (0.493)	0.650 (0.477)
Attended kindergarten	0.807 (0.395)	0.821 (0.383)	0.879 (0.327)	0.828 (0.378)
Has ever repeated a grade	0.629 (0.484)	0.566 (0.496)	0.528 (0.500)	0.577 (0.494)
Has breakfast everyday	0.353 (0.479)	0.469 (0.499)	0.391 (0.489)	0.422 (0.494)
Is always hungry at school	0.235 (0.424)	0.114 (0.318)	0.0363 (0.187)	0.134 (0.341)
Does the chores at home every day during academic year	0.387 (0.488)	0.286 (0.452)	0.258 (0.438)	0.309 (0.462)
Mother can read	0.284 (0.451)	0.375 (0.485)	0.407 (0.492)	0.355 (0.479)
Has a reading book at school	0.959 (0.199)	0.967 (0.177)	0.968 (0.177)	0.965 (0.184)
Has a math book at school	0.948 (0.221)	0.978 (0.146)	0.992 (0.0896)	0.972 (0.164)
Books at home	0.461 (0.499)	0.486 (0.500)	0.621 (0.486)	0.504 (0.500)
Age (in years)	12.247 (1.049)	12.556 (1.004)	12.407 (1.183)	12.442 (1.059)
Student' standardized test score in reading	-0.847 (0.897)	0.162 (0.770)	0.844 (0.780)	0.000 (1.000)
Student' standardized test score in math	-0.903 (0.762)	0.169 (0.777)	0.909 (0.808)	0.000 (1.000)
Student' standardized aggregate test score	-0.905 (0.833)	0.171 (0.755)	0.907 (0.757)	0.000 (1.000)
Panel B: Teachers and classrooms characteristics				
Female teacher	0.083 (0.282)	0.100 (0.304)	0.308 (0.480)	0.130 (0.338)
Teacher attended university	0.667 (0.482)	0.550 (0.504)	0.769 (0.439)	0.623 (0.488)
Teacher has the CAP	0.833 (0.381)	0.675 (0.474)	0.923 (0.277)	0.766 (0.426)
Teacher is permanent contract	0.667 (0.482)	0.650 (0.483)	0.769 (0.439)	0.675 (0.471)
Teacher has a secondary activity	0.292 (0.464)	0.325 (0.474)	0.154 (0.376)	0.286 (0.455)

Teachers' standardized test score in reading	0.017 (1.100)	-0.098 (1.008)	0.076 (0.918)	-0.033 (1.013)
Teachers' standardized test score in math	-0.168 (1.083)	0.00158 (1.021)	0.0799 (1.021)	-0.038 (1.031)
Teachers' standardized test score in teaching reading	0.066 (1.040)	0.009 (0.830)	0.323 (1.012)	0.080 (0.925)
Teachers' standardized test score in teaching math	0.381 (0.985)	0.383 (0.891)	0.362 (1.245)	0.379 (0.972)
Teacher years of experience	10.208 (5.816)	11.250 (5.882)	12.462 (6.628)	11.130 (5.959)
Multigrade classroom	0.542 (0.509)	0.250 (0.439)	0.308 (0.480)	0.351 (0.480)
Class size	29.875 (14.92)	33.975 (10.96)	34.154 (15.30)	32.727 (13.03)
Classroom equipment index	-0.348 (1.106)	0.226 (1.072)	0.0172 (0.810)	0.0121 (1.062)
Panel C: Principals and schools characteristics				
Has a university degree	0.753 (0.432)	0.747 (0.435)	0.718 (0.451)	0.743 (0.437)
Has the CAP	0.974 (0.159)	0.970 (0.170)	1.000 (0.000)	0.977 (0.151)
School has all 6 grades	0.881 (0.324)	0.944 (0.229)	1.000 (0.000)	0.937 (0.244)
Urban school	0.232 (0.423)	0.280 (0.450)	0.250 (0.434)	0.261 (0.439)
School is accessible all the academic year	0.874 (0.333)	0.973 (0.162)	1.000 (0.000)	0.950 (0.218)
School receives an inspection during the academic year	0.889 (0.314)	0.828 (0.378)	0.714 (0.453)	0.825 (0.380)
School teaches the official curriculum for reading	0.835 (0.372)	0.808 (0.394)	0.859 (0.349)	0.825 (0.380)
School teaches the official curriculum for math	0.835 (0.372)	0.764 (0.425)	0.960 (0.197)	0.820 (0.385)
School applies automatic grade promotion	0.889 (0.314)	0.881 (0.324)	0.778 (0.416)	0.865 (0.342)
School does not provide tutoring to students	0.152 (0.360)	0.153 (0.360)	0.0645 (0.246)	0.137 (0.344)
School has an annual budget	0.0851 (0.279)	0.222 (0.416)	0.0847 (0.279)	0.159 (0.365)
Has a school canteen	0.281 (0.450)	0.122 (0.327)	0.000 (0.000)	0.145 (0.352)

Notes: Authors calculations based on PASEC2019 data for Senegal

Appendix Table 3 : Simulations 1 and 2 estimates with empirical 95% confidence interval (using the aggregate score) – 5,000 replications

Statistics	Baseline	Simulation 1: Random shuffling at national level		Simulation 2: Random shuffling at regional level	
		Estimate	**95% Confidence Interval**	**Estimate**	**95% Confidence Interval**
Min	-2.648	-4.673	(-4.690; -4.656)	-4.501	(-4.514; -4.489)
Max	1.859	4.546	(4.530; 4.563)	4.297	(4.281; 4.312)
Mean	0.000	0.065	(0.064; 0.066)	0.079	(0.078; 0.080)
p10	-0.938	-2.160	(-2.166; -2.154)	-2.146	(-2.152; -2.140)
p25	-0.400	-1.093	(-1.097; -1.089)	-1.065	(-1.069; -1.061)
p50	0.089	0.057	(0.053; 0.060)	0.099	(0.096; 0.103)
p75	0.515	1.227	(1.223; 1.231)	1.268	(1.264; 1.272)
p90	0.771	2.306	(2.299; 2.312)	2.281	(2.275; 2.287)
SD	0.691	1.730	(1.728; 1.733)	1.703	(1.700; 1.705)

Notes: Authors calculations based on PASEC2019 data for Senegal

Appendix Table 4 : Effects of the simulations on the distribution of the aggregate score – 10,000 replications

Statistics	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		Random shuffling at national level	Random shuffling at regional level	Teachers with the best performing students replace teachers with the least performing students at the national level.	Teachers with the best performing students replace teachers with the least performing students at the regional level	High-skill teachers rotate with the ones with lower skills at the national level.	High-skill teachers rotate with the ones with lower skills at the regional level.	High-skill teachers are allocated to low-performing classrooms and vice-versa at the national level.	High-skill teachers are allocated to low-performing classrooms and vice-versa at the regional level.	More experienced teachers rotate with the less experienced ones at the national level.	More experienced teachers rotate with the less experienced ones at the regional level.	Most experienced teachers are allocated to low-performing classrooms and vice-versa at the national level.	Most experienced teachers are allocated to low-performing classrooms and vice-versa at the regional level.
Min	**-2.648**	4.553	4.319	4.109	5.571	4.273	4.534	4.165	4.166	4.878	4.576	4.192	4.576
Max	**1.859**	0.065	0.079	0.110	0.102	0.072	0.128	0.053	0.073	0.098	0.075	0.049	0.149
Mean	**0.000**	-4.680	-4.505	-4.286	-5.308	-4.042	-3.977	-4.750	-3.998	-5.228	-3.998	-4.394	-5.308
p10	**-0.938**	-2.163	-2.145	-1.873	-1.786	-2.285	-1.971	-2.076	-2.185	-2.198	-2.151	-2.105	-2.152
p25	**-0.400**	-1.093	-1.068	-1.064	-0.906	-1.452	-0.840	-1.144	-1.066	-1.022	-1.139	-1.209	-0.821
p50	**0.089**	0.059	0.100	0.150	0.175	0.209	0.044	-0.003	0.053	-0.042	0.055	-0.067	0.311
p75	**0.515**	1.226	1.269	1.200	1.045	1.487	1.147	1.347	1.135	1.456	1.166	1.248	1.267
p90	**0.771**	2.306	2.279	2.020	1.809	2.522	2.221	2.382	2.511	2.344	2.258	2.514	2.223
SD	**0.691**	1.732	1.705	1.619	1.545	1.781	1.548	1.709	1.670	1.867	1.699	1.787	1.679
Variation of mean score (a)	-	0.065	0.079	0.110	0.102	0.072	0.128	0.053	0.073	0.098	0.075	0.049	0.149
Variation of the SD (b)	-	1.041	1.014	0.928	0.854	1.090	0.858	1.018	0.980	1.176	1.009	1.096	0.988
(b)/(a)	**-**	***16.1***	***12.8***	***8.4***	***8.3***	***15.2***	***6.7***	***19.2***	***13.4***	***12.0***	***13.4***	***22.5***	***6.6***

Notes: Authors calculations based on PASEC2019 data for Senegal. p10, p25, p50, p75 and p90 are the 10^{th}, 25^{th}, 50^{th} (median), 75^{th} and 90^{th} percentiles, respectively.

Appendix Table 5 : Effects of the simulations on the distribution of the aggregate score, computed as the simple average of plausible values – 5,000 replications

Statistics	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		Random shuffling at national level	Random shuffling at regional level	Teachers with the best performing students replace teachers with the least performing students at the national level.	Teachers with the best performing students replace teachers with the least performing students at the regional level	High-skill teachers rotate with the ones with lower skills at the national level.	High-skill teachers rotate with the ones with lower skills at the regional level.	High-skill teachers are allocated to low-performing classrooms and vice-versa at the national level.	High-skill teachers are allocated to low-performing classrooms and vice-versa at the regional level.	More experienced teachers rotate with the less experienced ones at the national level.	More experienced teachers rotate with the less experienced ones at the regional level.	Most experienced teachers are allocated to low-performing classrooms and vice-versa at the national level.	Most experienced teachers are allocated to low-performing classrooms and vice-versa at the regional level.
Min	1.937	4.551	4.314	4.025	5.635	4.293	4.587	4.100	4.218	4.880	4.634	4.026	4.634
Max	0.000	0.064	0.077	0.109	0.102	0.070	0.124	0.052	0.071	0.096	0.074	0.050	0.147
Mean	-2.652	-4.664	-4.477	-4.163	-5.399	-4.049	-3.972	-4.750	-4.048	-5.265	-4.048	-4.484	-5.399
p10	-0.938	-2.139	-2.142	-1.818	-1.813	-2.269	-1.912	-2.098	-2.130	-2.185	-2.185	-2.066	-2.126
p25	-0.412	-1.082	-1.057	-1.061	-0.879	-1.423	-0.841	-1.096	-1.050	-1.027	-1.130	-1.207	-0.802
p50	0.085	0.053	0.097	0.141	0.165	0.199	0.032	-0.004	0.050	0.022	0.055	-0.041	0.306
p75	0.513	1.216	1.261	1.165	1.051	1.460	1.149	1.306	1.124	1.439	1.204	1.213	1.252
p90	0.780	2.288	2.273	1.994	1.735	2.518	2.247	2.367	2.551	2.340	2.228	2.526	2.200
SD	0.697	1.719	1.698	1.595	1.528	1.767	1.544	1.704	1.662	1.858	1.693	1.777	1.674
Variation of mean score (a)	-	0.064	0.077	0.109	0.102	0.070	0.124	0.052	0.071	0.096	0.074	0.050	0.147
Variation of the SD (b)	-	1.023	1.002	0.898	0.831	1.070	0.847	1.007	0.966	1.162	0.996	1.080	0.977
(b)/(a)	**-**	**16.0**	**13.0**	**8.3**	**8.1**	**15.2**	**6.9**	**19.5**	**13.6**	**12.1**	**13.4**	**21.7**	**6.6**

Notes: Authors calculations based on PASEC2019 data for Senegal. p10, p25, p50, p75 and p90 are the 10th, 25th, 50th (median), 75th and 90th percentiles, respectively.

Appendix Table 6 : Heterogeneous effects by topic across the 12 simulations

Statistics	(1) Random shuffling at national level	(2) Random shuffling at regional level	(3) Teachers with the best performing students replace teachers with the least performing students at the national level.	(4) Teachers with the best performing students replace teachers with the least performing students at the regional level	(5) High-skill teachers rotate with the ones with lower skills at the national level.	(6) High-skill teachers rotate with the ones with lower skills at the regional level.	(7) High-skill teachers are allocated to low-performing classrooms and vice-versa at the national level.	(8) High-skill teachers are allocated to low-performing classrooms and vice-versa at the regional level.	(9) More experienced teachers rotate with the less experienced ones at the national level.	(10) More experienced teachers rotate with the less experienced ones at the regional level.	(11) Most experienced teachers are allocated to low-performing classrooms and vice-versa at the national level.	(12) Most experienced teachers are allocated to low-performing classrooms and vice-versa at the regional level.
Panel A: Reading												
Variation of mean score (a)	0.063	0.081	0.110	0.102	0.068	0.130	0.056	0.077	0.100	0.079	0.039	0.143
Variation of the SD (b)	1.048	0.997	0.981	0.903	1.099	0.865	1.008	0.968	1.169	1.000	1.087	0.955
(b)/(a)	**16.5**	**12.3**	**8.9**	**8.9**	**16.3**	**6.6**	**18.0**	**12.7**	**11.7**	**12.7**	**28.2**	**6.7**
Panel B: Math												
Variation of mean score (a)	0.057	0.066	0.095	0.090	0.066	0.106	0.041	0.059	0.083	0.061	0.055	0.136
Variation of the SD (b)	0.912	0.917	0.753	0.706	0.941	0.761	0.921	0.872	1.046	0.902	0.984	0.903
(b)/(a)	**15.9**	**13.9**	**7.9**	**7.8**	**14.2**	**7.2**	**22.6**	**14.9**	**12.6**	**14.7**	**18.0**	**6.6**

Notes: Authors calculations based on PASEC2019 data for Senegal

Appendix Table 7 : Heterogeneous effects on girls and boys across the 12 simulations

Statistics	(1) Random shuffling at national level	(2) Random shuffling at regional level	(3) Teachers with the best performing students replace teachers with the least performing students at the national level.	(4) Teachers with the best performing students replace teachers with the least performing students at the regional level	(5) High-skill teachers rotate with the ones with lower skills at the national level.	(6) High-skill teachers rotate with the ones with lower skills at the regional level.	(7) High-skill teachers are allocated to low-performing classrooms and vice-versa at the national level.	(8) High-skill teachers are allocated to low-performing classrooms and vice-versa at the regional level.	(9) More experienced teachers rotate with the less experienced ones at the national level.	(10) More experienced teachers rotate with the less experienced ones at the regional level.	(11) Most experienced teachers are allocated to low-performing classrooms and vice-versa at the national level.	(12) Most experienced teachers are allocated to low-performing classrooms and vice-versa at the regional level.
Panel A: Girls												
Variation of mean score (a)	0.056	0.057	0.046	0.042	0.053	0.062	0.079	0.055	0.102	0.027	0.037	0.147
Variation of the SD (b)	1.059	1.034	0.960	0.895	1.128	0.875	1.020	0.996	1.146	1.059	1.115	0.977
(b)/(a)	**19.0**	**18.0**	**20.7**	**21.1**	**21.4**	**14.1**	**12.9**	**18.2**	**11.3**	**39.9**	**30.5**	**6.7**
Panel B: Boys												
Variation of mean score (a)	0.076	0.107	0.192	0.179	0.096	0.211	0.020	0.097	0.094	0.137	0.064	0.151
Variation of the SD (b)	1.017	0.986	0.889	0.804	1.044	0.837	1.016	0.962	1.215	0.946	1.076	1.004
(b)/(a)	**13.4**	**9.2**	**4.6**	**4.5**	**10.9**	**4.0**	**50.5**	**10.0**	**12.9**	**6.9**	**16.8**	**6.6**

Notes: Authors calculations based on PASEC2019 data for Senegal

Appendix Table 8 : Heterogeneous effects on students of rural and urban schools across the 12 simulations

Statistics	(1) Random shuffling at national level	(2) Random shuffling at regional level	(3) Teachers with the best performing students replace teachers with the least performing students at the national level.	(4) Teachers with the best performing students replace teachers with the least performing students at the regional level	(5) High-skill teachers rotate with the ones with lower skills at the national level.	(6) High-skill teachers rotate with the ones with lower skills at the regional level.	(7) High-skill teachers are allocated to low-performing classrooms and vice-versa at the national level.	(8) High-skill teachers are allocated to low-performing classrooms and vice-versa at the regional level.	(9) More experienced teachers rotate with the less experienced ones at the national level.	(10) More experienced teachers rotate with the less experienced ones at the regional level.	(11) Most experienced teachers are allocated to low-performing classrooms and vice-versa at the national level.	(12) Most experienced teachers are allocated to low-performing classrooms and vice-versa at the regional level.
Panel A: Rural												
Variation of mean score (a)	0.076	0.082	0.130	0.078	0.071	0.047	0.136	-0.014	0.071	0.062	0.154	0.089
Variation of the SD (b)	0.981	0.945	0.915	0.824	1.095	0.868	0.967	0.902	1.067	0.971	0.997	0.920
(b)/(a)	**12.8**	**11.5**	**7.0**	**10.6**	**15.4**	**18.3**	**7.1**	**-**	**15.0**	**15.6**	**6.5**	**10.4**
Panel B: Urban												
Variation of mean score (a)	0.031	0.070	0.055	0.173	0.073	0.355	-0.183	0.320	0.175	0.113	-0.249	0.318
Variation of the SD (b)	1.190	1.185	0.986	0.949	1.090	0.791	1.181	1.170	1.485	1.132	1.378	1.171
(b)/(a)	**38.0**	**16.8**	**17.8**	**5.5**	**15.0**	**2.2**	**-**	**3.7**	**8.5**	**10.1**	**-**	**3.7**

Notes: Authors calculations based on PASEC2019 data for Senegal

Appendix Table 9 : Heterogeneous effects on students of poor and rich families across the 12 simulations

Statistics	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Random shuffling at national level	Random shuffling at regional level	Teachers with the best performing students replace teachers with the least performing students at the national level.	Teachers with the best performing students replace teachers with the least performing students at the regional level	High-skill teachers rotate with the ones with lower skills at the national level.	High-skill teachers rotate with the ones with lower skills at the regional level.	High-skill teachers are allocated to low-performing classrooms and vice-versa at the national level.	High-skill teachers are allocated to low-performing classrooms and vice-versa at the regional level.	More experienced teachers rotate with the less experienced ones at the national level.	More experienced teachers rotate with the less experienced ones at the regional level.	Most experienced teachers are allocated to low-performing classrooms and vice-versa at the national level.	Most experienced teachers are allocated to low-performing classrooms and vice-versa at the regional level.
Panel A: Poor												
Variation of mean score (a)	-0.015	-0.054	0.000	-0.055	-0.115	-0.018	-0.050	-0.089	0.098	0.031	-0.019	0.000
Variation of the SD (b)	0.956	0.945	0.934	0.683	1.044	0.633	1.029	0.959	1.068	0.834	1.109	0.954
(b)/(a)	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**11.0**	**26.8**	**-**	**-**
Panel B: Rich												
Variation of mean score (a)	0.145	0.213	0.221	0.261	0.259	0.274	0.156	0.236	0.099	0.120	0.116	0.298
Variation of the SD (b)	1.131	1.069	0.920	0.996	1.112	1.050	1.011	0.982	1.318	1.198	1.102	1.009
(b)/(a)	**7.8**	**5.0**	**4.2**	**3.8**	**4.3**	**3.8**	**6.5**	**4.2**	**13.3**	**10.0**	**9.5**	**3.4**

Notes: Authors calculations based on PASEC2019 data for Senegal

Appendix Table 10 : Variation of selected deciles and quartiles across the 12 simulations

Variation with respect to baseline value	(1) Random shuffling at national level	(2) Random shuffling at regional level	(3) Teachers with the best performing students replace teachers with the least performing students at the national level.	(4) Teachers with the best performing students replace teachers with the least performing students at the regional level	(5) High-skill teachers rotate with the ones with lower skills at the national level.	(6) High-skill teachers rotate with the ones with lower skills at the regional level.	(7) High-skill teachers are allocated to low-performing classrooms and vice-versa at the national level.	(8) High-skill teachers are allocated to low-performing classrooms and vice-versa at the regional level.	(9) More experienced teachers rotate with the less experienced ones at the national level.	(10) More experienced teachers rotate with the less experienced ones at the regional level.	(11) Most experienced teachers are allocated to low-performing classrooms and vice-versa at the national level.	(12) Most experienced teachers are allocated to low-performing classrooms and vice-versa at the regional level.
p10	-1.223	-1.209	-0.936	-0.849	-1.348	-1.034	-1.139	-1.248	-1.261	-1.213	-1.167	-1.215
p25	-0.693	-0.666	-0.664	-0.506	-1.053	-0.441	-0.745	-0.667	-0.622	-0.739	-0.810	-0.422
p50	-0.033	0.010	0.061	0.085	0.120	-0.045	-0.092	-0.036	-0.131	-0.034	-0.156	0.222
p75	0.713	0.753	0.686	0.530	0.972	0.632	0.833	0.621	0.942	0.651	0.734	0.752
p90	1.535	1.510	1.249	1.038	1.751	1.450	1.611	1.740	1.573	1.487	1.743	1.452

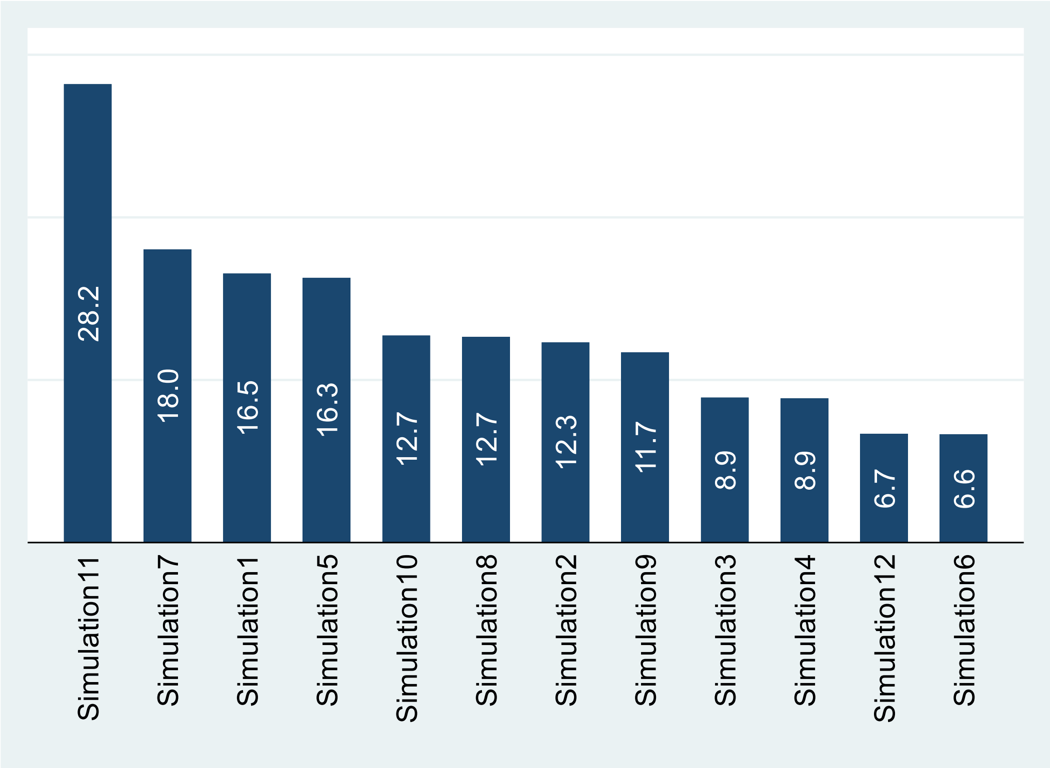
Notes: Authors calculations based on PASEC2019 data for Senegal

Appendix Table 11 : Key teacher-level variables in low and average performing classrooms (compared to high performing classrooms) after simulations 11 and 12

		Teacher's score in reading	Teacher's score in math	Teacher's aggregate score	Teacher is female	Teacher's experience	Teacher's absenteeism
Baseline	Low performing classrooms	-0.059	-0.248	-0.195	-0.224*	-0.368	0.358
		(0.353)	(0.358)	(0.358)	(0.115)	(0.337)	(0.368)
	Average performing classrooms	-0.174	-0.078	-0.174	-0.208*	-0.198	0.245
		(0.327)	(0.332)	(0.332)	(0.106)	(0.312)	(0.341)
Simulation 11	Low performing classrooms	-0.258	-0.076	-0.216	-0.301***	2.394***	-0.055
		(0.344)	(0.360)	(0.355)	(0.111)	(0.147)	(0.370)
	Average performing classrooms	-0.587*	-0.082	-0.415	-0.310***	0.829***	-0.076
		(0.319)	(0.334)	(0.329)	(0.103)	(0.137)	(0.343)
Simulation 12	Low performing classrooms	-0.529	-0.694**	-0.740**	-0.183	1.065***	0.348
		(0.347)	(0.342)	(0.348)	(0.114)	(0.315)	(0.365)
	Average performing classrooms	-0.510	0.002	-0.365	-0.233**	0.562*	0.478
		(0.322)	(0.317)	(0.323)	(0.106)	(0.292)	(0.339)

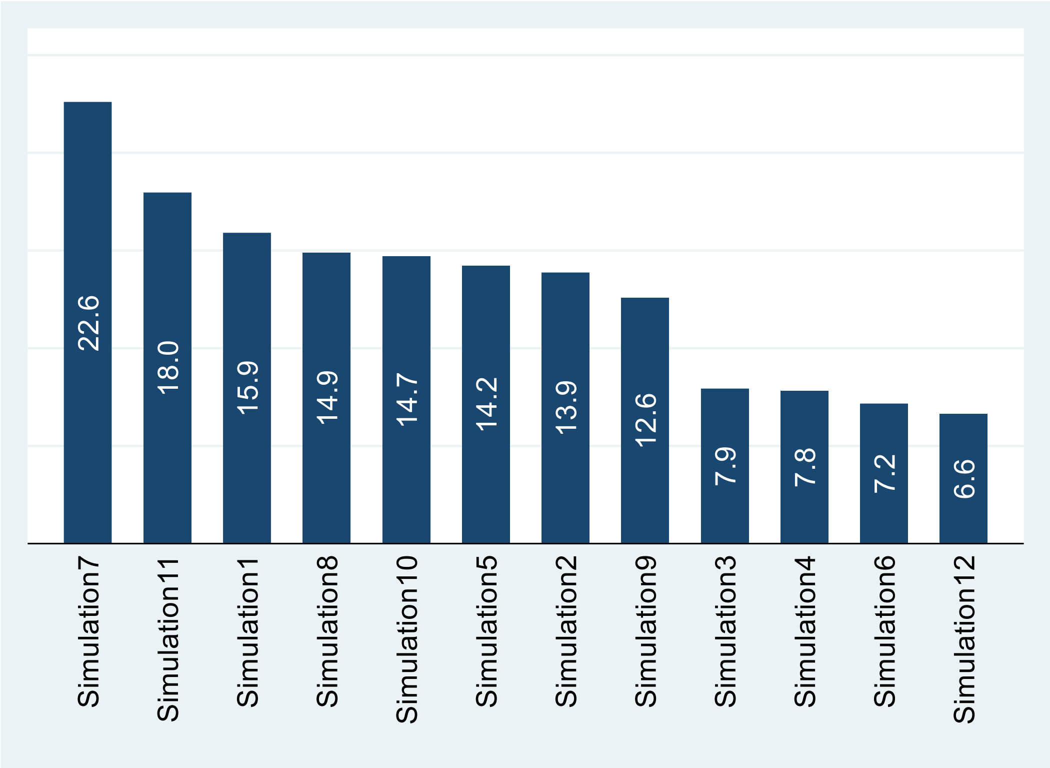
Notes: Authors calculations based on PASEC2019 data for Senegal.
, **, * indicate $p < 0.10$, $p < 0.05$, $p < 0.01$, respectively.*

Appendix Figure 1: Equity cost per unit of quality improvement, Reading score



Note: Simulations details are provided in sub-section 4.2 of this paper.

Appendix Figure 2: Equity cost per unit of quality improvement, Math score



Note: Simulations details are provided in sub-section 4.2 of this paper.

University of Antwerp
IOB | Institute of Development Policy