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THE ADDED VALUE OF MORE ACCURATE PREDICTIONS FOR SCHOOL RANKINGS

by Fritz Schiltz[1], Paolo Sestito[2], Tommaso Agasisti[3] and Kristof De Witte[4]

Abstract

School rankings based on value-added (VA) estimates are subject to prediction errors, since VA is defined as the difference between predicted and actual performance. We introduce a more flexible random forest (RF), rooted in the machine learning literature, to minimize prediction errors and to improve school rankings. Monte Carlo simulations demonstrate the advantages of this approach. Applying the proposed method to data on Italian middle schools indicates that school rankings are sensitive to prediction errors, even when extensive controls are added. RF estimates provide a low-cost way to increase the accuracy of predictions, resulting in more informative rankings, and better policies.

JEL Classification: I21, C50
Keywords: value-added, school rankings, machine learning, Monte Carlo

Contents

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1 Introduction

School rankings are increasingly being used as a means to strengthen accountability in the education sector. Value-added (VA) estimates are considered a best practice to rank schools and have been adopted in the United Kingdom, the Netherlands, and the USA. Estimating VA is a high-stakes statistical exercise, as rankings based on VA estimates often determine personnel decisions or school closure (Angrist, Hull, Pathak, & Walters, 2017).

Two caveats are worth noting with respect to school rankings based on VA estimates. First, earlier research has argued that nonrandom selection of students into classes and schools (sorting) biases VA estimates (Rothstein, 2009). Including controls can partially account for this bias, in those cases where sorting is on observables (Koedel, Mihaly & Rockoff, 2015). Let alone data issues, it is generally difficult to tell which, and how variables influence student sorting.[1] Second, VA estimation requires predictions, as they indicate the difference between actual and predicted performance. Hence, VA estimates are subject to prediction errors. Particularly, nonlinear interactions between important inputs in the education production function might result in unrealistic predictions when conventional linear estimates are used. Moreover, this issue of prediction errors remains in place, even when all relevant sorting variables are included.

This paper proposes an alternative approach to estimate school VA and to obtain rankings. In particular, we introduce 'random forests' which add flexibility by capturing nonlinearities and complex interactions (Breimann, 2001). A recent trend towards machine learning in economics advocates such models for predictions, as they may allow for more effective ways to model complex relationships (Mullainathan & Spiess, 2017; Varian, 2014). Especially when modelling the education production function, discontinuous relationships and nonlinear interaction effects are more naturally accommodated by a random forest. This machine learning approach does not require prior knowledge on the education production function (inside the 'black box'). Given the same set of variables, this added flexibility results in more accurate predictions.

We use Monte Carlo simulations to demonstrate that random forest estimates reflect more closely the VA of schools compared to conventional methods, resulting in more reliable school rankings. We then illustrate the benefits of the proposed approach using data on Italian middle schools. In addition to the availability of rich data, the Italian case is particularly interesting as there is an ongoing policy debate on the most appropriate statistics to publish as a guide for parents. This paper contributes to this public debate, which is also present in many other countries (e.g. the Netherlands, the UK, the US). Our simulations and empirical application indicate that school rankings based on conventional VA estimates are very sensitive to prediction errors. More accurate VA estimates result in more informative rankings for parents, and more impact of policy decisions. Moreover, our results indicate that the improved accuracy from more flexible random forest estimates is comparable to the accuracy gains from adding more data in the conventional approach. This suggests a low-cost way to improve VA estimates, particularly when limited data is available. The proposed method is likely to be fruitful in other public sector activities such as health and social services, where entities are ranked and evaluated based on

[1]Other studies have exploited data from lotteries to reduce bias in VA estimates (Deming, 2014; Angrist et al., 2017).

value-added estimates.[2]

2 Empirical strategy

Estimating school value-added (VA) implies predicting individual student test scores and averaging the prediction errors for each school:

$$A_i = \beta^{'}\mathbf{X}_i + v_i \tag{1}$$

$$\text{where } v_i = \mu_j + \epsilon_i \tag{2}$$

with $A_{i,t}$ the test score (e.g. mathematics or reading) for student i, $\mathbf{X}_i$ the set of control variables, μ_j the effect of school j, and ϵ_i the unobserved error in scores, unrelated to the school VA. The VA of school j (μ_j), can then be obtained by averaging the prediction errors for school j:[3]

$$\hat{\mu}_j = \frac{1}{N}\sum_{i=1}^{N}(A_i - \hat{A}_i) \tag{3}$$

$$\text{where } \hat{A}_i = \beta^{'}\mathbf{X}_i \tag{4}$$

Schools that, on average, manage to help students achieve test scores A_i beyond their prediction $\hat{A}_i$ are considered to be adding value to the test scores, and vice versa. Student characteristics $\mathbf{X}_i$ and ϵ_i may be correlated with μ_j in the likely event that students self-select into schools. Accounting for such sorting behavior is the key challenge in obtaining unbiased VA estimates.

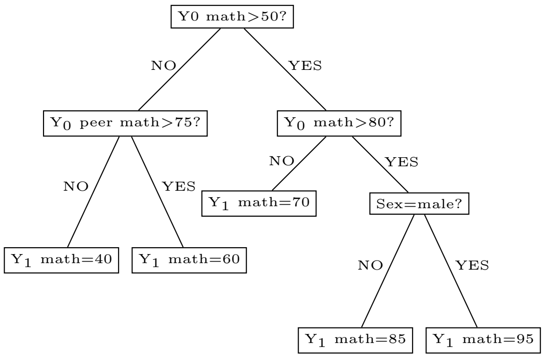
If all sorting variables could be observed, and are included in $\mathbf{X}_i$, the conventional OLS estimate of $\beta^{'}\mathbf{X}_i$ would potentially still lead to ϵ_i and μ_j being correlated due to anomalies in the education production function. For example, decreasing returns to scale not captured by (1), can result in erroneous predictions of $\hat{A}_i$, and hence $\hat{\mu}_j$. This source of bias in VA estimates can be reduced by increasing the accuracy of predictions $(A_i - \hat{A}_i)$. Using regression trees we can improve predictions for students, given the same set of variables, and without the need to specify a functional form for the education production function.

Regression trees can be seen as a set of rules resulting from recursive partitioning observations into groups, or 'leaves' - incorporating nonlinearities and interactions by construction (Breiman et al., 1984). These leaves are chosen to minimize the residual sum of squares (RSS) of the predictions. Figure 1 illustrates how regression trees add flexibility when predicting test scores. In this example tree, mathematics scores in Y_1 (here [0-100]) are predicted using individual and peers' scores in Y_0, and sex. In this fictitious problem, a split at the mathematics score in Y_0 equal to 50 is best able to reduce the RSS compared to all other binary splits of all variables. Therefore, it is chosen as the first split, at the top of the tree. Along the same lines, an additional split on sex only reduces the RSS for high achieving students (Y_0 math > 80). As illustrated by this example, regression trees allow for nonlinear relationships between variables and the predicted outcome. Once the regression tree is built using recursive partitioning, the predicted outcome of a new observation then equals the average of

[2] An R template code for other applications is available upon request.

[3] Alternative approaches are often applied to mitigate bias in VA estimates of small schools, for example by shrinking estimates towards the overall mean (Angrist et al., 2017; Guarino et al., 2015) or by using multilevel models. The latter approach is followed by the UK government to rank schools in England on VA (Ray, 2006).

Figure 1: An example of a regression tree to predict mathematics scores in Y_1



Notes: Outcome variable is mathematics score in Y_1 [0-100]. The regression tree displays the fictitious result of recursive partitioning using Y_0 scores, peer scores in Y_0 and sex.

the leaf where we end up by following the set of rules embodied by the tree. For example, a student with a math score in Y_0 above 50 and above 80 is predicted to score 85 if the student is a girl.

The accuracy of regression trees can be substantially improved by constructing them iteratively. A random forest (RF) constructs a large number of trees using randomly drawn samples and randomly drawn predictors as candidates at each split (Breiman, 2001; James et al., 2013). We will use random forests in the empirical application and Monte Carlo simulations to improve predictions, and hence, VA estimates.

3 Data and specification

We construct school rankings for Italian middle schools by estimating each school's value added for mathematics. We use data from the National Institute for the Evaluation of the Educational System of Education and Training (INVALSI). It contains extensive information on all Italian students and schools for the 2013 cohort. INVALSI resembles to the OECD PISA data, although data are collected for all students in Italy, and at different moments in time. It was designed in this way for the purpose of estimating the value added of schools and ranking them. Every student is observed twice in the data: grade 5 data is collected at the end of primary school, and grade 8 data at the end of middle school. Hence, the change in mathematics test scores between grade 5 and grade 8 provides a measure of the added value of middle schools for mathematics.[4]

We first estimate a *baseline* model to predict grade 8 mathematics test scores including only lagged test scores (i.e. in grade 5). This specification corresponds to VA in its most common form (Todd & Wolpin, 2003). Using these predictions (and prediction errors), a VA estimate can be obtained for each school. We follow Lefgren & Sims (2012) by including lagged test scores for both mathematics and reading as explanatory variables, to improve predictions of grade

[4]A more comprehensive description can be found in earlier studies using this dataset, see for example De Simone (2013, p.14) or Bertoni, Brunello, & Rocco (2013, p.66-67).

Table 1: Comparing accuracy of predictions

	Absolute error			Mean squared error	
Model:	RF	Conventional	Diff	RF	Conventional
baseline	15.34	23.78	-8.43***	421	979
final	8.92	22.54	-13.63***	140	869

Notes: Predicted variable is mathematics score in grade 8 (mean=198, SD=38). *Diff* indicates the difference in absolute prediction errors. *** indicates significance at 1%.

8 test scores in mathematics. Next, we estimate a *final* model which can be seen as the 'contextual' VA used in England to obtain school rankings (Ray, 2006), accounting for differences in student characteristics and peers, and hence reducing bias from student sorting. In particular, we include a set of student characteristics (immigrant status, sex, socio-economic status, grade repetition before grade 5), and the same set of variables averaged at class and school level to capture differences in peer composition. In addition, we also include the relative previous position of students in their class, and the relative previous position of students' classes in their schools. We do not claim to perfectly control for nonrandom selection of students into classes and schools, although the richness of INVALSI allows a more complete set of controls than commonly included. We estimate both baseline and final models using a conventional OLS approach and using a random forest for the sake of comparison.[5]

4 Results and discussion

4.1 Monte Carlo simulations

In order to compare the ability of conventional and random forest estimates to reflect the school value-added (VA), we iteratively generate a sample of students and group them into schools. First, we compare the accuracy of conventional and random forest predictions at the student level ($A_i - \hat{A}_i$). Second, we obtain VA estimates by averaging these prediction errors. We then compare the VA estimates for each school relative to the true value added in our simulation ($\mu_j - \hat{\mu_j}$). Finally, we compare the school rankings obtained from the conventional and the RF approach to the true ranking. As detailed in the appendix of this paper, three parameters define the data-generating process: the effect size of school VA, the nonlinearity in the education production function, and the degree to which students sort into schools. Simulations over this set of parameters indicate that RF provides more accurate predictions of student test scores. Moreover, when the effect size of school VA is relatively modest, and the education production function is not strictly linear, we provide evidence that RF estimates are also better able to reflect the VA of schools, and are hence more informative about school rankings. This information gain is especially pronounced when students sort into schools.

[5]When estimating the random forest, we set the number of trees equal to 500 and the number of variables as split candidates at the square root of the number of variables (default).

Table 2: Identifying bottom and top schools

	Q25		
Model:	RF	Conventional	Diff
baseline	0.84	0.82	4%*
final	1	0.85	13%***
	Q75		
Model:	RF	Conventional	Diff
baseline	0.79	0.74	5%***
final	1	0.81	18%***

Notes: Percentages indicate the share of schools classified as bottom (Q25) or top (Q75) by both benchmark rankings and the evaluated model. Benchmark rankings are those obtained from the final RF model. Bootstrapped SEs: *,**,*** indicate significance at 10%, 5 and 1%.

4.2 Ranking Italian schools

Table 1 compares the accuracy of predictions, in terms of absolute errors and mean squared error (MSE).[6] Clearly, the random forest predictions outperform conventional predictions for both baseline and final models. Adding more data, i.e. going from baseline to final, reduces prediction errors. However, adding flexibility, i.e. going from conventional to RF, seems to reduce these errors even further, and significantly. The higher accuracy of RF predictions reveals the limited ability of the conventional estimate to adequately capture the complex education production function, and casts serious doubt on accountability prescriptions based on such measures.

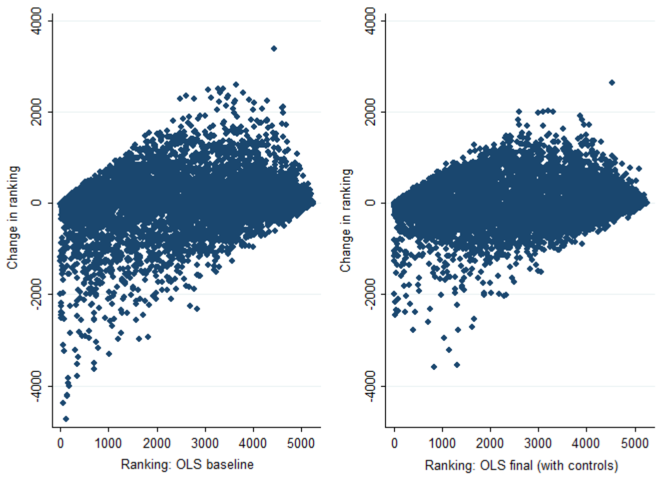
Building on the findings from the Monte Carlo simulations, we set the school ranking obtained from the final RF model as the benchmark ranking. In Figure 2, we compare rankings obtained from conventional estimates (baseline and final) to this benchmark. Clearly, major changes occur when rankings are based on RF estimates instead of conventional estimates of VA. These changes are especially pronounced in schools ranked at the bottom by conventional estimates, and even more so at the top. Also, including the extensive set of controls in the final specification appears to only partially resolve the diverging rankings. In the right hand side panel, after adding all controls to account for selection on observables, schools ranked highly by the conventional VA still experience large (downward) rank changes when compared to the RF rank.

Table 2 presents the share of schools 'correctly' identified as ranked in the bottom or top quartile. We define 'correct' as a match with the classification obtained from the final RF, considering its ability to minimize prediction errors. For example, 81% of the schools ranked in the top quartile by the final conventional estimate are also classified in this group using the final RF estimate. As can be seen from Table 2, RF estimates of VA provide a significantly better classifier for low- and top-performing schools. This already suggests a major advantage of ranking schools based on RF estimates when limited data is available.

For policy makers, school rankings can be particularly useful to identify best practices or to target low-performing schools. In practice, VA measures

[6] Our results are analogous for reading test scores, and for alternative specifications of the conventional model (linear-log, and adding higher degree polynomials for mathematics and reading scores in grade 5). Alternative definitions of school VA (school median VA, average of reading and mathematics VA) also indicate analogous results.

Figure 2: Rank changes when improving predictions.



Notes: Schools ranked in terms of VA estimates: baseline conventional OLS estimates (left) and final conventional OLS estimates (right). We ranked all 5,249 schools using their VA estimate. We obtain VA estimates for conventional and RF predictions by averaging the difference between actual and predicted scores, as in (3). The school ranked 1$^{\text{st}}$ exhibits the largest VA. Vertical axes indicate the change in rank when final RF estimates are used to obtain the ranking of schools.

are used to rank schools and close down schools that end up at the bottom of this ranking. The impact of any such policy depends on the ability of rankings to identify schools at the bottom and at the top of the unknown VA distribution. To illustrate the usefulness of the proposed approach, we provide back-of-the-envelope calculations of closing the average school in the bottom quartile and enrolling its students in the average school in the top quartile.[7] Using the rankings obtained from the final RF estimates, we find that achievement gains could be as large as 0.21 standard deviations (SD). However, when baseline conventional estimates of VA are used to obtain rankings, this effect reduces to 0.19 SD, as schools are being closed that are not actually in the bottom and students are sent to schools that are not actually in the top. A school closure policy based on RF estimates and limited data would yield the same benefits (0.20 SD) as a policy based on conventional estimates using the full set of controls. This implies that the policy impact can be increased by 0.01 SD when extensive controls are added to the specification, and the impact can be increased by another 0.01 SD when flexibility is added to estimate VA and to rank schools. Although this effect appears negligible, our calculations suggest that RF predictions provide an effective, low-cost way to improve rankings, irrespective of the data available.

[7]Following Angrist et al. (2017), we ignore possible transition effects such as disruption due to school closure, peer effects from changes in school composition, and other factors that might inhibit replication of successful schools.

5 Conclusion

For parents and policy makers, the main concern regarding school rankings is whether they provide a valid tool to compare school quality. However, since 'value-added' (VA) is defined as the difference between predicted and actual performance, prediction errors can result in biased rankings. This paper introduced random forests to estimate school VA, as this approach more naturally accommodates discontinuous relationships and nonlinear interaction effects in the education production function. Using Monte Carlo simulations we demonstrated that random forest estimates not only provide better individual predictions, but also provide a better approximation of school VA compared to conventional estimates, in nearly all parameter configurations. Starting from these findings, we compared rankings of Italian middle schools for random forest and conventional estimates. Clearly, rankings were strongly divergent, to an extent that could not be accounted for by including a set of controls at the individual, class, and school level. Finally, we provided back-of-the-envelope calculations to assess the impact of a hypothetical school closure policy in Italy, strictly based on rankings. Our calculations indicate that the impact of this policy is increased by 0.01 standard deviations when random forest estimates are used to rank schools instead of conventional estimates.

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Appendix: Monte Carlo simulations

In order to compare the ability of conventional and random forest estimates to reflect the school value-added (VA), we iteratively ($B = 100$) generate 10,000 student observations, grouped in 100 schools. First, we compare the accuracy of predictions at the student level, measured as the mean squared error (MSE). Second, we compare the MSE of VA estimates for each school relative to the true value added in our simulation. Finally, we compare the rankings obtained from the conventional approach and the RF rankings to the true ranking using rank order correlation coefficients (Spearman's ρ and Kendall's τ).

1 Data Generating Process (DGP)

We define the data generating process (DGP) of student achievement in Y_1 as a function of previous test scores, peer test scores in Y_0, and the added value of schools. For each student, we calculate test scores in Y_1 as follows:

$$\begin{aligned} &\hat{M}_{1i} = f(M_0, M_0^p, \mu_s) + \epsilon_i \\ &\text{with } \epsilon_i \sim N(0,1) \end{aligned} \tag{1}$$

1.1 Functional form: α

The functional form underlying the DGP and connecting mathematics test scores in Y_0 and Y_1 is specified as a linear combination of a linear and non-linear function. In particular:

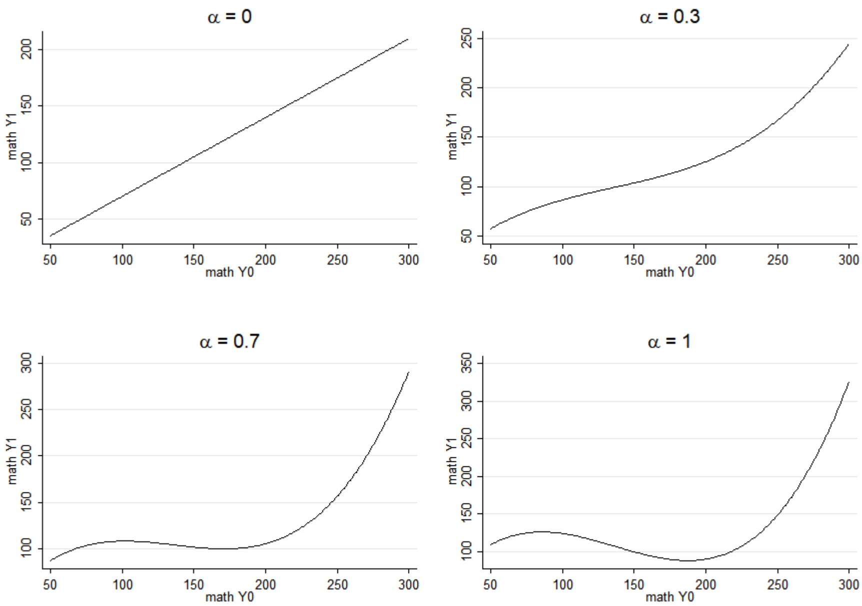
$$\begin{aligned} \hat{M}_{1i} =& (1-\alpha)[\beta_M(M_{0i} + \beta_p M_{0i}^p)] \\ &+ \alpha[\sum_1^k \beta_{Mk}(M_{0i} + \beta_p M_{0i}^p)^k] \\ &+ \mu_s + \epsilon_i \end{aligned} \tag{2}$$

We set $k = 4$, obtaining a fourth degree polynomial function in the second part of (2). As this part is clearly a nonlinear function of M, α indicates the degree of nonlinearity in the education production function (EPF). For $\alpha = 0$, (2) reduces to a strictly linear specification, whereas $\alpha = 1$ imposes the polynomial functional form on the EPF. In our simulations, mathematics test scores in Y_0 are drawn from the normal distribution, truncated corresponding to the empirical distribution in Italy. Figure 1 displays the relationship between mathematics test scores in Y_0 and Y_1, for different values of α.

1.2 Student sorting: γ

In reality, students sort into schools as parents consider school composition an important determinant of school choice. Therefore, we simulate different degrees of school sorting, indicated by γ. For each student, a random number is drawn around the student's mathematics score (M_0), with standard deviation $1000(\gamma)^4$). Based on this individual number, students are assigned to equally sized schools. For $\gamma = 1$, students are assigned to schools in a random manner,

Figure 1: Functional form of the EPF as a function of α.



avoiding bias from student sorting. As γ approaches 0, students sort themselves into schools based on mathematics scores in Y_0. For $\gamma = 0$, sorting is perfect: the first x spots available in the first school are taken by the x highest performers. Next, the leave-out-mean is calculated for each student and included in the DGP as M_{0i}^p. A student's test score in Y_1 is influenced by his peers (M_{0i}^p) following the same functional form, see (2). Depending on the value of β_p, student sorting affects predictions of M_1. In accordance with the literature on peer effects (Sacerdote, 2014), we evaluate two scenarios where peer effects are either nonexistent (β_p=0) or moderate (β_p=0.1), as "half the studies do not find evidence of peer effects in test scores [and] approximately half the studies find either modest or large effects on test scores" (Sacerdote, 2014, p. 269). For $\gamma = 1$, there is no correlation between M_{0i} and M_{0i}^p, while this correlation approaches 1 as $\gamma \to 0$ (for $\beta_p \neq$0). In Italy, we measure a correlation of 0.38 between current mathematics test scores and school-level average test scores. This corresponds to a level of $\gamma \approx 0.55$.

1.3 School VA: μ

The added value μ_s is assumed to be constant for all students within the same school, but different across schools. We assume the VA of schools to be independent of individual (M_{0i}) and peer (M_{0i}^p) test scores. Hence, μ_s follows a deterministic rule:

$$\mu_s = \begin{cases} j, & \text{if } j = \text{even} \\ -j, & \text{if } j = \text{odd} \end{cases} \tag{3}$$

Where j indicates the school number, randomly assigned to students grouped in the same school, following the sorting rule implied by γ. Hence, μ_s is uncorrelated to M_{0i} and M_{0i}^p. School VA as defined in (3) is rescaled to reflect the literature on school effects (Hattie, 2008, p.74), suggesting a small (range of 0.1 SD of M_0), or intermediate (range of 0.3 SD) effect. In Italy, the difference in VA between the average school in the top quartile and the average school in the bottom quartile is estimated to equal approximately 0.2 standard deviations (see 4.2).

2 Results

Tables 1 and 2 present the simulation results for different DGPs (averaged over B). Each table contains results for the conventional OLS approach and the RF approach advocated in this paper. Values of α and γ between 0 and 1 are considered, and we allow different scenarios for the importance of μ_s in the DGP. All conventional and RF estimates are obtained by including both the individual score (M_0) and the leave-out-mean (M_0^p) as predictors of scores in Y_1 (M_1). In the first scenario (Table 1), we simulate the trivial case where peer effects do not affect individual achievement, $\beta_p = 0$. Hence, M_1 is defined by the school value-added μ_s, previous scores M_0, and measurement error ϵ. In the second, and more realistic, scenario, we set $\beta_p = 0.1$ such that student sorting affects scores in Y_1 through peer effects (Table 2). Under both scenarios, we can draw a similar general conclusion: The advantage of RF over conventional estimates is especially pronounced when the education production function is not *strictly* linear, if students are not randomly assigned to schools (i.e. students sort into schools), and the value-added of schools does not exceed 0.3 standard deviations. If the above conditions *do* hold, jointly, it can be preferable to apply the conventional approach to estimate the school VA, and rank schools accordingly. Under all alternative parameter configurations, RF estimates provide a more accurate representation by minimizing prediction errors. For clarity, bold notation indicates configurations where RF estimates are preferred over OLS conventional estimates in the Monte Carlo simulations.

Table 1a: MCS results: β_p=0, μ_s=0.1

	OLS	RF	OLS	RF	OLS	RF	OLS	RF	OLS	RF	OLS	RF
	0		0.2		0.4		0.6		0.8		1	
	Accuracy of test score predictions: MSE											
0	**2.29**	**0.32**	**2.29**	**0.32**	**2.3**	**0.43**	**2.29**	**0.54**	**2.29**	**0.56**	**2.29**	**0.56**
0.2	**30.66**	**0.32**	**30.61**	**0.32**	**30.52**	**0.43**	**30.63**	**0.54**	**30.63**	**0.56**	**30.57**	**0.56**
0.4	**115.35**	**0.33**	**116.46**	**0.32**	**115.66**	**0.44**	**115.83**	**0.55**	**115.59**	**0.57**	**116.05**	**0.56**
0.6	**256.99**	**0.32**	**257.63**	**0.32**	**257.65**	**0.46**	**258.64**	**0.55**	**257.19**	**0.58**	**257.22**	**0.58**
0.8	**454.43**	**0.33**	**454.83**	**0.33**	**455.63**	**0.5**	**455.05**	**0.61**	**456.85**	**0.63**	**457.7**	**0.62**
1	**709.99**	**0.33**	**714.79**	**0.33**	**706.92**	**0.55**	**712.69**	**0.66**	**711.38**	**0.69**	**713.05**	**0.68**
	Accuracy of VA estimates: MSE											
0	0.02	1.3	0.03	1.24	0.02	0.83	0.02	0.68	0.02	0.64	0.02	0.62
0.2	**28.16**	**1.3**	**28.04**	**1.23**	**12.45**	**0.84**	0.44	0.68	0.31	0.64	0.3	0.62
0.4	**112.68**	**1.3**	**113.09**	**1.24**	**49.93**	**0.85**	**1.78**	**0.71**	**1.12**	**0.65**	**1.15**	**0.63**
0.6	**252.86**	**1.3**	**253.09**	**1.24**	**112.28**	**0.89**	**3.91**	**0.75**	**2.5**	**0.67**	**2.53**	**0.66**
0.8	**449.4**	**1.3**	**448.59**	**1.24**	**199.38**	**0.89**	**6.87**	**0.75**	**4.53**	**0.7**	**4.57**	**0.67**
1	**703.15**	**1.3**	**704.15**	**1.24**	**309.86**	**0.87**	**10.89**	**0.74**	**7.24**	**0.67**	**7.15**	**0.66**
	Rank order correlations: Spearman's ρ											
0	0.99	0.17	0.99	0.73	0.99	0.89	0.99	0.92	0.99	0.92	0.99	0.93
0.2	0.35	0.16	**0.35**	**0.73**	**0.43**	**0.89**	**0.87**	**0.92**	**0.9**	**0.92**	**0.91**	**0.93**
0.4	0.2	0.16	**0.2**	**0.72**	**0.28**	**0.89**	**0.67**	**0.91**	**0.74**	**0.92**	**0.73**	**0.93**
0.6	**0.15**	**0.15**	**0.14**	**0.72**	**0.2**	**0.87**	**0.5**	**0.9**	**0.59**	**0.92**	**0.58**	**0.92**
0.8	**0.12**	**0.17**	**0.1**	**0.72**	**0.16**	**0.88**	**0.4**	**0.91**	**0.47**	**0.91**	**0.46**	**0.91**
1	**0.1**	**0.15**	**0.11**	**0.73**	**0.13**	**0.88**	**0.35**	**0.91**	**0.38**	**0.92**	**0.38**	**0.92**
	Rank order correlations: Kendall's τ											
0	0.92	0.11	0.92	0.53	0.93	0.71	0.93	0.75	0.93	0.76	0.93	0.77
0.2	0.25	0.1	**0.25**	**0.53**	**0.32**	**0.71**	**0.69**	**0.75**	**0.73**	**0.76**	**0.73**	**0.76**
0.4	0.14	0.11	**0.14**	**0.52**	**0.2**	**0.7**	**0.48**	**0.74**	**0.54**	**0.76**	**0.54**	**0.77**
0.6	0.11	0.1	**0.1**	**0.52**	**0.14**	**0.67**	**0.35**	**0.72**	**0.41**	**0.75**	**0.41**	**0.75**
0.8	**0.08**	**0.11**	**0.07**	**0.52**	**0.11**	**0.68**	**0.28**	**0.73**	**0.32**	**0.74**	**0.32**	**0.74**
1	**0.07**	**0.1**	**0.08**	**0.53**	**0.09**	**0.69**	**0.24**	**0.73**	**0.26**	**0.75**	**0.26**	**0.75**

Table 1b: MCS results: β_p=0, μ_s=0.3

	OLS	RF	OLS	RF	OLS	RF	OLS	RF	OLS	RF	OLS	RF
	0		0.2		0.4		0.6		0.8		1	
	Accuracy of test score predictions: MSE											
0	**12.65**	**0.33**	**12.65**	**0.35**	**12.61**	**0.97**	**12.67**	**1.55**	**12.61**	**1.79**	**12.63**	**1.89**
0.2	**40.21**	**0.33**	**41.3**	**0.35**	**40.46**	**0.98**	**40.93**	**1.54**	**40.95**	**1.79**	**41.05**	**1.85**
0.4	**126.47**	**0.33**	**127.29**	**0.36**	**125.68**	**0.95**	**126.8**	**1.51**	**125.95**	**1.75**	**126.31**	**1.85**
0.6	**267.57**	**0.33**	**270.24**	**0.36**	**267.19**	**0.95**	**267.49**	**1.48**	**267.33**	**1.72**	**267.85**	**1.84**
0.8	**465.01**	**0.33**	**465**	**0.36**	**464.1**	**0.98**	**467.87**	**1.52**	**465.91**	**1.76**	**465.43**	**1.9**
1	**722.22**	**0.33**	**727.02**	**0.36**	**720.86**	**1.04**	**720.53**	**1.58**	**722.04**	**1.88**	**725.49**	**1.94**
	Accuracy of VA estimates: MSE											
0	0.12	11.71	0.12	11.28	0.15	8.29	0.1	6.76	0.13	6.26	0.15	6.08
0.2	**28.17**	**11.69**	**28.14**	**11.29**	**12.57**	**8.2**	0.58	6.81	0.41	6.28	0.41	6.14
0.4	**112.62**	**11.69**	**112.22**	**11.28**	**50.21**	**8.4**	1.86	6.98	1.22	6.43	1.28	6.21
0.6	**254.2**	**11.71**	**254.02**	**11.28**	**112.39**	**8.57**	3.98	7.18	2.6	6.63	2.61	6.33
0.8	**449.66**	**11.67**	**447.91**	**11.25**	**198.03**	**8.58**	6.94	7.26	4.62	6.63	4.69	6.35
1	**705.13**	**11.71**	**705.51**	**11.27**	**309.68**	**8.53**	**10.97**	**7.26**	**7.19**	**6.55**	**7.09**	**6.44**
	Rank order correlations: Spearman's ρ											
0	0.99	0.48	0.99	0.75	0.99	0.87	1	0.91	0.99	0.91	0.99	0.92
0.2	0.63	0.48	**0.65**	**0.74**	**0.75**	**0.87**	0.98	0.91	0.98	0.91	0.98	0.92
0.4	**0.45**	**0.48**	**0.46**	**0.75**	**0.54**	**0.86**	0.93	0.9	0.95	0.91	0.95	0.91
0.6	**0.33**	**0.48**	**0.34**	**0.75**	**0.44**	**0.86**	**0.87**	**0.89**	0.91	0.9	0.91	0.91
0.8	**0.28**	**0.47**	**0.28**	**0.75**	**0.36**	**0.86**	**0.81**	**0.9**	**0.85**	**0.91**	**0.85**	**0.91**
1	**0.24**	**0.48**	**0.24**	**0.75**	**0.32**	**0.87**	**0.73**	**0.9**	**0.8**	**0.91**	**0.79**	**0.91**
	Rank order correlations: Kendall's τ											
0	0.95	0.33	0.95	0.54	0.95	0.67	0.96	0.73	0.95	0.74	0.95	0.75
0.2	0.48	0.33	**0.49**	**0.54**	**0.58**	**0.68**	0.88	0.73	0.89	0.74	0.89	0.75
0.4	**0.33**	**0.33**	**0.34**	**0.54**	**0.41**	**0.67**	0.78	0.72	0.81	0.73	0.81	0.74
0.6	**0.24**	**0.33**	**0.25**	**0.55**	**0.32**	**0.66**	**0.69**	**0.71**	**0.73**	**0.73**	**0.73**	**0.74**
0.8	**0.2**	**0.33**	**0.2**	**0.55**	**0.26**	**0.67**	**0.61**	**0.72**	**0.66**	**0.73**	**0.66**	**0.74**
1	**0.17**	**0.33**	**0.17**	**0.55**	**0.23**	**0.67**	**0.54**	**0.72**	**0.6**	**0.73**	**0.6**	**0.73**

Table 2a: MCS results: β_p=0.1, μ_s=0.1

	OLS	RF	OLS	RF	OLS	RF	OLS	RF	OLS	RF	OLS	RF
	0		0.2		0.4		0.6		0.8		1	
	Accuracy of test score predictions: MSE											
0	**2.29**	**0.32**	**2.29**	**0.32**	**2.29**	**0.43**	**2.3**	**0.54**	**2.29**	**0.56**	**2.29**	**0.56**
0.2	**73.84**	**0.32**	**73.87**	**0.32**	**65.92**	**0.45**	**52.91**	**0.57**	**51.17**	**0.58**	**51.07**	**0.58**
0.4	**285.21**	**0.33**	**286.84**	**0.33**	**257.77**	**0.49**	**204.14**	**0.62**	**196.9**	**0.63**	**196.26**	**0.62**
0.6	**640.54**	**0.33**	**642.1**	**0.33**	**571.54**	**0.56**	**455.96**	**0.69**	**440.78**	**0.71**	**438.45**	**0.69**
0.8	**1132.48**	**0.33**	**1138**	**0.33**	**1013.75**	**0.65**	**810.14**	**0.81**	**781.72**	**0.82**	**780.61**	**0.8**
1	**1782.1**	**0.33**	**1779.02**	**0.33**	**1589.48**	**0.77**	**1254.64**	**0.98**	**1232.51**	**0.97**	**1220.83**	**0.93**
	Accuracy of VA estimates: MSE											
0	0.02	1.3	0.02	1.23	0.02	0.86	0.02	0.7	0.02	0.65	0.02	0.62
0.2	**70.92**	**1.3**	**70.62**	**1.23**	**32.08**	**0.85**	**0.94**	**0.69**	0.52	0.65	0.5	0.62
0.4	**281.99**	**1.3**	**282.03**	**1.23**	**129.48**	**0.87**	**3.68**	**0.7**	**1.98**	**0.66**	**1.89**	**0.62**
0.6	**635.37**	**1.3**	**633.7**	**1.23**	**286.25**	**0.87**	**8.53**	**0.72**	**4.41**	**0.66**	**4.39**	**0.64**
0.8	**1122.71**	**1.3**	**1125**	**1.23**	**511.37**	**0.88**	**15.26**	**0.73**	**7.55**	**0.67**	**7.74**	**0.64**
1	**1769.24**	**1.3**	**1760.3**	**1.23**	**801.6**	**0.87**	**23.64**	**0.74**	**12.24**	**0.68**	**11.84**	**0.65**
	Rank order correlations: Spearman's ρ											
0	0.99	0.17	0.99	0.73	0.99	0.88	0.99	0.91	0.99	0.92	0.99	0.93
0.2	0.26	0.16	**0.27**	**0.73**	**0.34**	**0.88**	**0.78**	**0.91**	**0.85**	**0.92**	**0.86**	**0.93**
0.4	**0.13**	**0.17**	**0.15**	**0.72**	**0.2**	**0.86**	**0.55**	**0.91**	**0.63**	**0.91**	**0.65**	**0.93**
0.6	**0.1**	**0.17**	**0.12**	**0.73**	**0.16**	**0.85**	**0.41**	**0.9**	**0.47**	**0.91**	**0.47**	**0.91**
0.8	**0.09**	**0.17**	**0.08**	**0.73**	**0.11**	**0.85**	**0.3**	**0.89**	**0.38**	**0.91**	**0.38**	**0.91**
1	**0.08**	**0.15**	**0.07**	**0.73**	**0.1**	**0.84**	**0.24**	**0.88**	**0.31**	**0.9**	**0.3**	**0.91**
	Rank order correlations: Kendall's τ											
0	0.93	0.11	0.93	0.53	0.93	0.69	0.93	0.74	0.93	0.75	0.93	0.77
0.2	0.19	0.11	**0.19**	**0.53**	**0.25**	**0.69**	**0.59**	**0.74**	**0.66**	**0.75**	**0.66**	**0.77**
0.4	**0.09**	**0.12**	**0.11**	**0.52**	**0.14**	**0.67**	**0.39**	**0.73**	**0.44**	**0.74**	**0.46**	**0.76**
0.6	**0.07**	**0.12**	**0.08**	**0.52**	**0.11**	**0.66**	**0.28**	**0.72**	**0.33**	**0.73**	**0.32**	**0.75**
0.8	**0.06**	**0.11**	**0.06**	**0.53**	**0.07**	**0.65**	**0.21**	**0.71**	**0.26**	**0.73**	**0.26**	**0.74**
1	**0.06**	**0.1**	**0.05**	**0.52**	**0.06**	**0.65**	**0.17**	**0.7**	**0.21**	**0.73**	**0.2**	**0.74**

Table 2b: MCS results: β_p=0.1, μ_s=0.3

	0		0.2		0.4		0.6		0.8		1	
	OLS	RF	OLS	RF	OLS	RF	OLS	RF	OLS	RF	OLS	RF
Accuracy of test score predictions: MSE												
0	**12.66**	**0.33**	**12.63**	**0.35**	**12.59**	**0.96**	**12.61**	**1.53**	**12.64**	**1.76**	**12.63**	**1.87**
0.2	**84.44**	**0.33**	**84.54**	**0.36**	**75.51**	**0.99**	**63**	**1.57**	**61.31**	**1.81**	**60.95**	**1.89**
0.4	**296.86**	**0.33**	**296.9**	**0.36**	**267.54**	**1.05**	**213.96**	**1.62**	**208.36**	**1.88**	**207.48**	**1.97**
0.6	**652.72**	**0.33**	**652.94**	**0.36**	**584.72**	**1.11**	**466.06**	**1.67**	**451.76**	**1.93**	**450.35**	**2.02**
0.8	**1151.83**	**0.33**	**1143.72**	**0.37**	**1029.15**	**1.21**	**820.03**	**1.81**	**798.49**	**2.07**	**790.87**	**2.14**
1	**1771.82**	**0.33**	**1798.95**	**0.37**	**1602.43**	**1.34**	**1278.43**	**2**	**1235.65**	**2.2**	**1229.39**	**2.31**
Accuracy of VA estimates: MSE												
0	0.12	11.71	0.13	11.27	0.14	8.32	0.11	6.82	0.14	6.36	0.17	6.14
0.2	**70.63**	**11.67**	**70.58**	**11.27**	**31.99**	**8.28**	1.04	6.84	0.56	6.28	0.62	6.05
0.4	**282.29**	**11.68**	**281.44**	**11.25**	**128.66**	**8.26**	3.95	6.85	2.04	6.21	2.02	6.04
0.6	**636.37**	**11.69**	**633.44**	**11.23**	**288.54**	**8.37**	**8.47**	**6.96**	4.53	6.37	4.43	6.06
0.8	**1134.79**	**11.71**	**1119.65**	**11.18**	**514.65**	**8.3**	**15.03**	**7**	**7.86**	**6.33**	**7.94**	**6.14**
1	**1749.08**	**11.66**	**1765.42**	**11.24**	**804.77**	**8.27**	**23.64**	**6.96**	**12.07**	**6.42**	**12.13**	**6.06**
Rank order correlations: Spearman's ρ												
0	1	0.49	0.99	0.75	0.99	0.86	1	0.9	0.99	0.91	0.99	0.92
0.2	0.53	0.47	**0.52**	**0.75**	**0.62**	**0.86**	0.96	0.9	0.98	0.92	0.98	0.92
0.4	**0.34**	**0.47**	**0.33**	**0.75**	**0.44**	**0.86**	**0.87**	**0.9**	0.93	0.92	0.93	0.92
0.6	**0.25**	**0.48**	**0.26**	**0.76**	**0.34**	**0.85**	**0.79**	**0.9**	**0.86**	**0.91**	**0.86**	**0.92**
0.8	**0.21**	**0.47**	**0.2**	**0.76**	**0.27**	**0.86**	**0.69**	**0.9**	**0.78**	**0.91**	**0.78**	**0.92**
1	**0.18**	**0.48**	**0.19**	**0.76**	**0.23**	**0.86**	**0.6**	**0.9**	**0.71**	**0.91**	**0.71**	**0.92**
Rank order correlations: Kendall's τ												
0	0.95	0.34	0.95	0.54	0.95	0.66	0.96	0.72	0.95	0.74	0.95	0.74
0.2	0.39	0.33	**0.39**	**0.55**	**0.47**	**0.67**	0.84	0.72	0.87	0.74	0.87	0.75
0.4	**0.25**	**0.33**	**0.24**	**0.55**	**0.32**	**0.67**	**0.7**	**0.72**	0.76	0.75	0.76	0.75
0.6	**0.18**	**0.33**	**0.19**	**0.55**	**0.24**	**0.66**	**0.6**	**0.72**	**0.66**	**0.74**	**0.67**	**0.75**
0.8	**0.15**	**0.32**	**0.15**	**0.55**	**0.19**	**0.67**	**0.5**	**0.71**	**0.58**	**0.74**	**0.58**	**0.74**
1	**0.13**	**0.33**	**0.13**	**0.56**	**0.16**	**0.67**	**0.43**	**0.73**	**0.52**	**0.74**	**0.51**	**0.75**

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