# An Analysis of Past Data of School Boards

A report prepared by the Indian Statistical Institute

## 1 Introduction

In India, there are various boards at the 10+2 level, including the CBSE, the ICSE and the state boards, each conducting a separate examination. The syllabus, marking scheme and difficulty level of these examinations may vary across the boards, and also within each board across years. Suppose we wish to compare the scores of students from different boards. In order to make this possible, we need to formulate a model and state its assumptions clearly. We give below a model and a set of assumptions, and check their validity using data on scores of students from different boards. Unfortunately, our analysis of data from some past examinations of several boards shows that the required assumptions do not hold, implying lack of comparability of scores from different boards in India.

# 2 Model and assumptions needed for comparability of scores

Suppose that there are k common subjects in a number of boards. We are interested in the comparability of the scores in a subject for different boards. We assume that for the *i*th subject  $(1 \le i \le k)$ , there exists an unobserved variable  $W_i$ , which we interpret as the merit variable corresponding to that subject. Suppose that the score  $(X_i)$  of an individual in that subject in his/her board examination is approximately a function of  $W_i$ . Then

$$X_i \approx g_i(W_i). \tag{1}$$

Here  $W_i$  is an attribute of the student (depending on knowledge and understanding of the specific subject, schooling, study hours, intelligence etc.) and  $g_i$  relates to the examination procedure corresponding to the *i*th subject. Two students may obtain different scores in two different examinations because of the difference in their merit (different  $W_i$ ) or because of the difference in the examination procedure (different  $g_i$ ).

If we intend to compare the scores from various boards, we need certain assumptions about  $W_i$  and  $g_i$  to hold. Two natural assumptions for this model set up are as given below.

#### Assumption 1

The function  $g_i$  is monotonically increasing. In other words, the scores of the students are expected to increase from less meritorious to more meritorious students in any particular subject.

#### Assumption 2

The joint distribution of  $(W_1, W_2, \ldots, W_k)$  for the students is the same irrespective of the board where they appear for examination. This assumption is crucial if the scores of students from different boards have to be comparable.

## 3 Checking the validity of the assumptions

Assumption 2 implies that if we look at the joint distribution of  $(W_i, W_j)$  for two subjects *i* and *j*  $(i \neq j)$ , then this distribution should be the same across various boards. This implies that the nature of dependence between  $W_i$  and  $W_j$  would be the same across various boards. Since, by Assumption 1,  $X_i$  and  $X_j$ , the scores in the *i*th and the *j*th subjects, are monotonic functions of  $W_i$  and  $W_j$  respectively, and the rank function preserves the relative order, we may measure the dependence between  $W_i$  and  $W_j$  by the rank correlation of  $X_i$  and  $X_j$ . Under our assumptions, the rank correlation between any pair of subject scores should be nearly the same for different boards. On the other hand, if these rank correlations differ significantly across different boards, it will indicate violation of the assumptions.

We find that this criterion is actually violated for the data on mathematics, physics and chemistry scores for four different boards over the years 2008 and 2009.

### 4 Data analysis

Figures 1 and 2 show the plots of the distribution of scores in six subjects over two different years (i.e., 2008 and 2009) for four different boards (i.e., CBSE, ICSE, Tamil Nadu board and West Bengal board). For each of these plots, the horizontal axis represents the different values of scores (normalized to the scale of 0 to 100), while the vertical axis represents the proportion of scores less than or equal to that value.

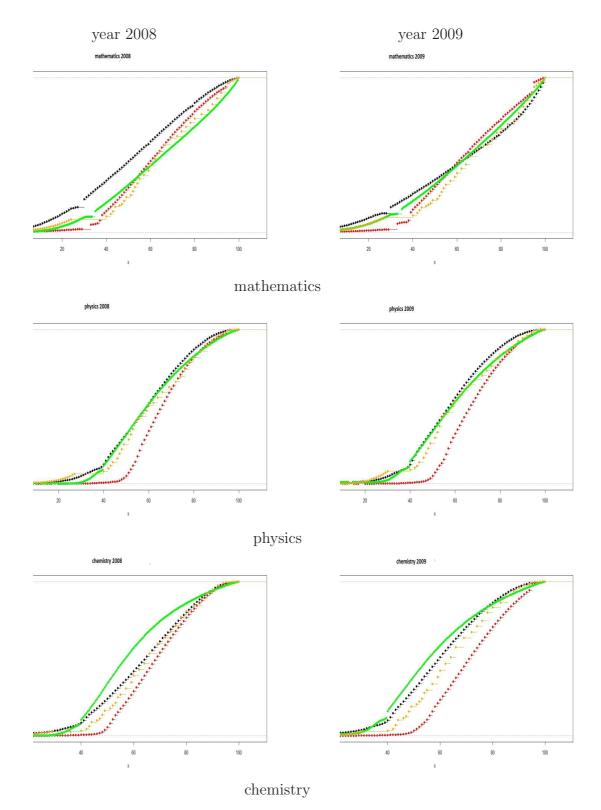
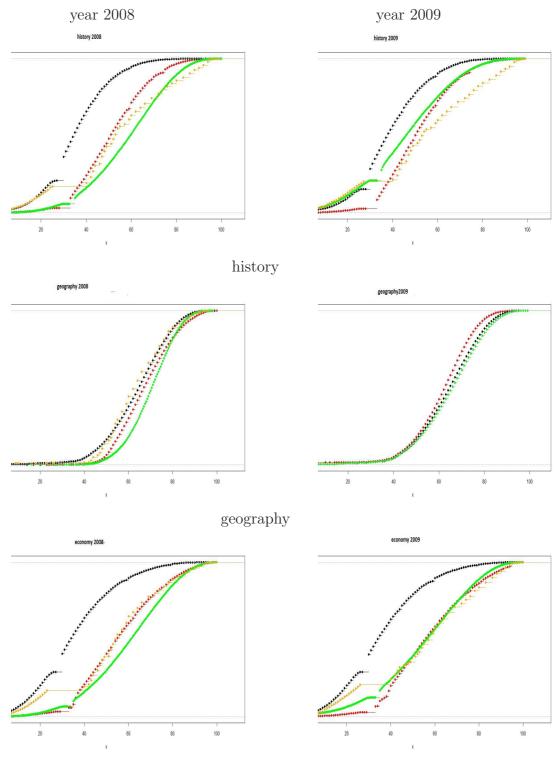


Figure 1: Distribution of scores in mathematics, physics and chemistry for various boards (CBSE, ICSE, Tamil Nadu and West Bengal). All scores are scaled to a total of 100.



economics.eps

Figure 2: Distribution of scores in history, geography and economics for various boards (CBSE, ICSE, Tamil Nadu and West Bengal). All scores are scaled to a total of 100.

From Figures 1 and 2, we have certain interesting observations that we list below.

- For some of the subjects, there is a clear difference in the score distribution across the various boards. For example, the proportion of students receiving high scores in history is far larger in the ICSE and the CBSE boards than in the West Bengal board.
- In most cases, there is a sharp jump in the graph around scores in the range of 30-35, which is possibly due to the practice of providing grace marks to pass a student.
- In subjects like mathematics, physics, chemistry and geography, a substantial proportion of students obtain high scores, while in history and economics, the proportion of students getting high scores may be large or small depending on the board.

Now, we present three bar charts describing the correlation pattern among the subjects physics, chemistry and mathematics for different boards and years.

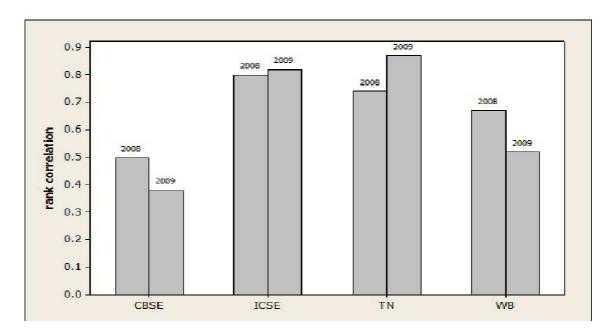


Figure 3: Rank correlation between physics and mathematics scores for different boards and years

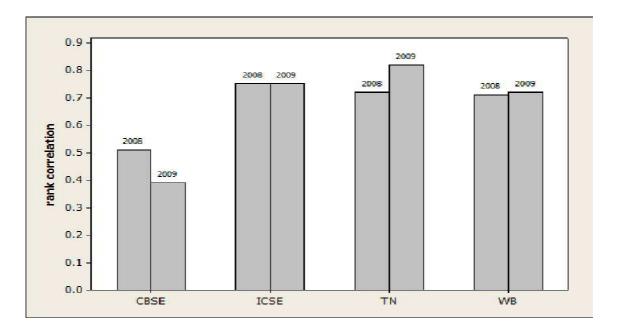


Figure 4: Rank correlation between chemistry and mathematics scores for different boards and years

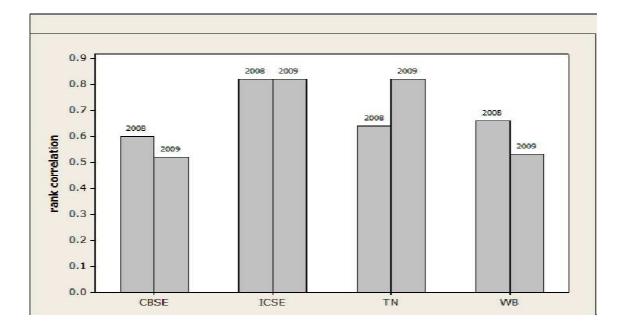


Figure 5: Rank correlation between chemistry and physics scores for different boards and years

It is clear from Figures 3, 4 and 5 that for each pair of subjects, there is significant variation in the rank correlation values across the boards, while the values are fairly stable across years for a specific board. (This is an indication that the scores from various boards do not satisfy our assumptions 1 and 2 and hence are not comparable.)

We now examine the rank correlation only for scores that are above the 50th percentiles in the two subjects in a pair.

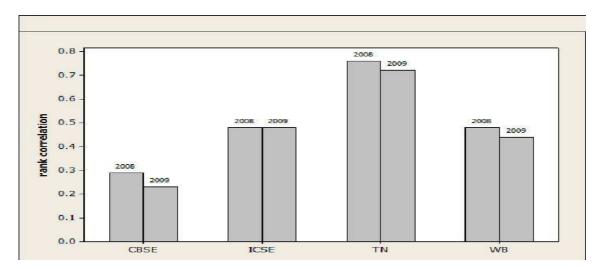


Figure 6: Rank correlation between physics and mathematics scores above 50th percentiles for different boards and years

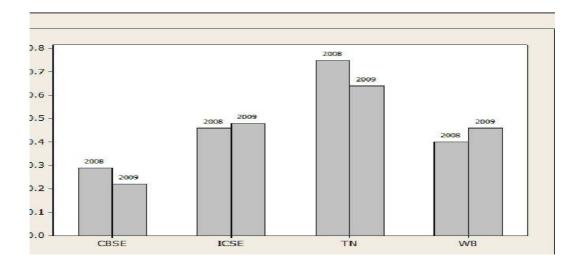


Figure 7: Rank correlation between chemistry and mathematics scores above 50th percentile for different boards and years

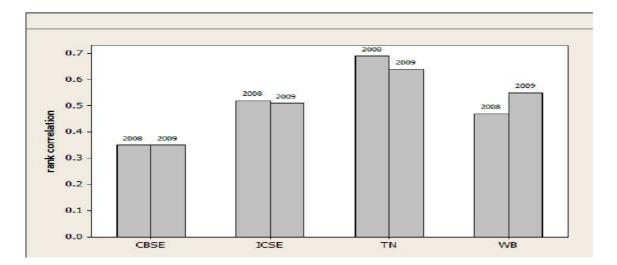


Figure 8: Rank correlation between physics and chemistry above 50th percentile for different boards and years

We observe from Figures 6, 7 and 8 that the variation in rank correlation values across the boards become more prominent than what was observed in Figures 3, 4 and 5. These variations are statistically significant – the p-values obtained by one-way ANOVA being 0.00004, 0.00064 and 0.00048 for the pairs physics-mathematics, mathematics-chemistry and physics-chemistry, respectively.

Since the subject scores do not appear to be comparable, the question of combining them for comparability of aggregate scores across the boards does not arise.