

Assessing the impact of computer ownership and access to internet on educational achievement in Indonesia

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Introduction

Indonesia, a middle-income country, faces the challenge of educating a workforce capable of engaging in higher-value added economic activities, sustaining economic growth and producing more diversified goods and services. The Indonesian government as well as the World Bank have highlighted that Indonesia does not now possess a workforce of sufficient training and technical expertise required for a more advanced economy that relies less on agriculture and extractive commodities and more on high value-added goods and services. Unless it can overcome this hurdle, sustained economic growth is at risk. While increasing educational achievement country-wide is a generational, long-term endeavor with no easy short-cuts or fixes, there are interventions that may increase educational achievement in the near term and potentiate greater achievement in the future. We explore the impact of computer ownership and access to the internet, adjusted for wealth levels, on educational achievement in Indonesia with a view to assessing whether interventions in those two factors can help to improve educational achievement in the country. To do so, we use the year 2018 [Programme for International Student Assessment \(PISA\)](#) survey carried out by Organization of Economic Development and Cooperation (OECD) worldwide every three years. We use test scores and accompanying data on student computer ownership, access to internet and wealth from the year-2018 survey to determine their impact on educational achievement as measured by the test scores.

The Data

The PISA survey data comes from the *learningtower* library (v1.0.1), acquired with the R statistical language and the RStudio IDE (v2023.12.0 Build 369). It consists of 11,819 observations with two (2) binary categorical factor variables – *computer* and *internet* – for computer ownership and internet access, respectively; one continuous, numerical test score response variable – *mean_TestScore* – created by taking the mean of the individual math, reading

and science test scores; and one continuous, numerical covariate variable, *wealth*. Univariate data statistics and plots are provided in Appendix A.

Methodology

We use a crossed, fixed-effects design with binary factor predictor variables *computer* and *internet*, and covariate *wealth*, applying an unequal-slopes ANCOVA model to assess the impact on the test score response variable *mean_TestScore* while accounting for the effect of the covariate. The initial, full ANCOVA model was reduced until all terms achieved significance at 0.05 level. The model is fitted with the *Anova()* function from the *car* library using Type 3 sums of squares. Pairwise mean comparisons, contrasts and confidence intervals are calculated at 0.05 level with the Bonferroni method. The final ANCOVA model table, means and contrasts results are provided in Appendix B. Model fit diagnostics, found in Appendix C, are satisfactory.

Results

The final ANCOVA model shows that the three, two-way interaction terms

computer:internet, *computer:wealth* and *internet:wealth* are significant at 95%

confidence. The *computer:internet* interaction shows that mean test scores for the four term treatments are all significantly different, with a low of 378 points for students with no computer and no internet access, to a high of 421 points for students with both a computer and internet access. All six factor level contrasts are significant. They range from an increase of 43 points in

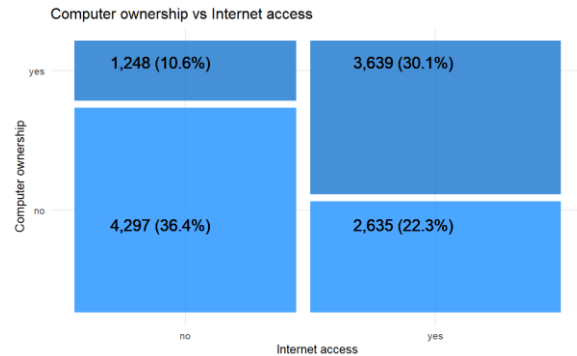


Figure 1 – Computer ownership vs. Internet Access

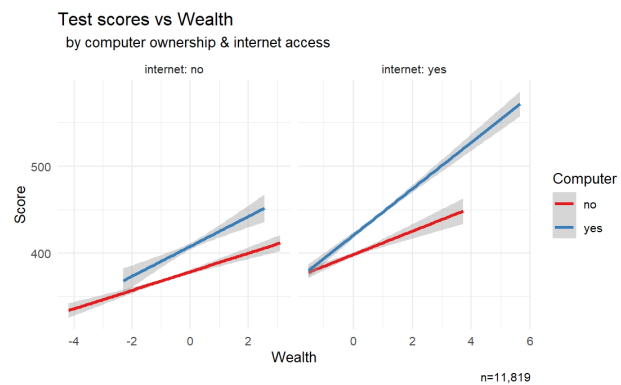


Figure 2 – Test Scores vs. Wealth by computer ownership

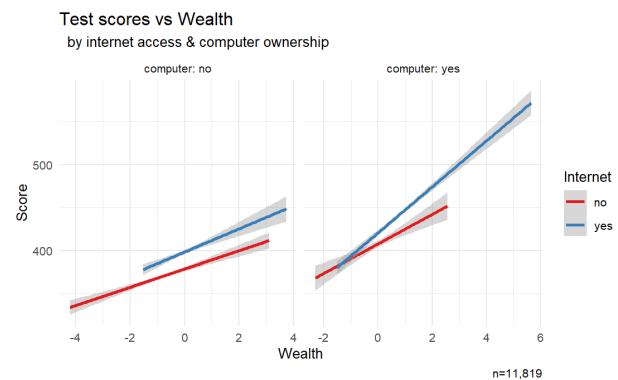


Figure 3 – Test Scores vs. Wealth by internet access

test scores by students with both a computer and internet access relative to students with no computer and no internet access, to a decrease of 9 points by students who have no computer and have internet access relative to students who have no internet access and have a computer. Results across contrasts show computer ownership has a greater impact on test scores than internet access.

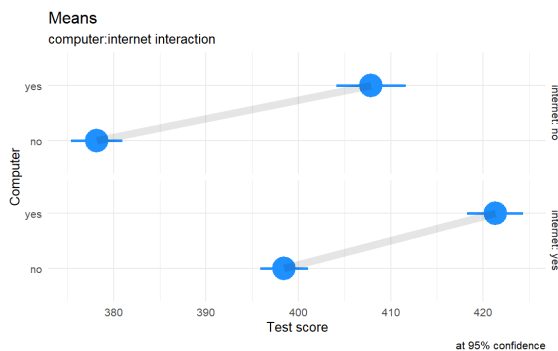


Figure 4 – Means, computer:internet interaction

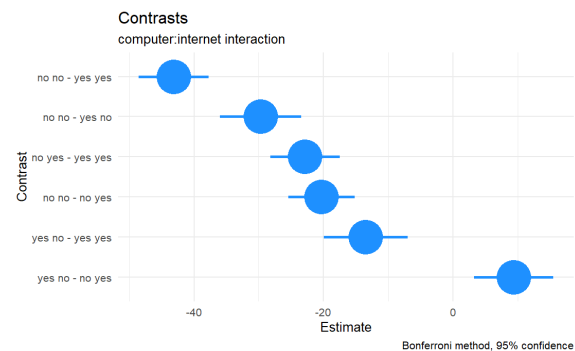


Figure 5 – Contrasts, computer:internet interaction

The *computer:wealth* interaction shows that mean test scores at covariate levels -1, 0, +1 and +2 standard deviations (SD) from the mean are significantly different, and that the differences increase with increasing wealth. They range from 376 points for students with no computer at -1 SD from the mean to 461 for students with a computer at +2 SD from the mean. All contrasts save for the one at level -2 SD wealth are significant. They range from 8 points for students at -1 SD wealth level to 24 points for students at +2 SD wealth level. Results across contrasts show that the greater the wealth, the greater the mean test score increase computer ownership.

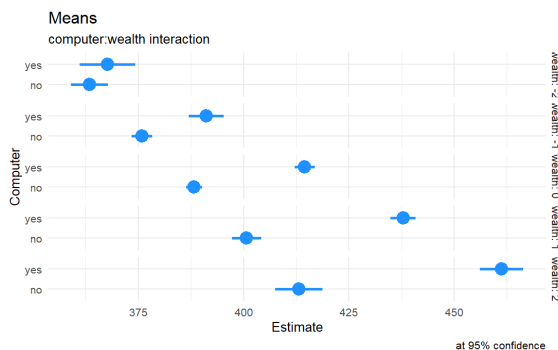


Figure 6 – Means, computer:wealth interaction

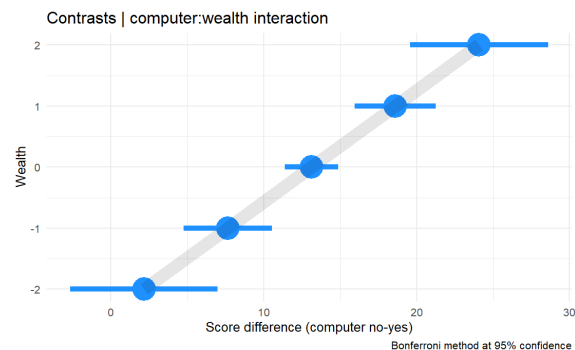


Figure 7 – Contrasts, computer:wealth interaction

The *internet:wealth* interaction shows that mean test scores at covariate levels -1, 0, +1 and +2 standard deviations (SD) from the mean are significantly different, and that the differences increase with increasing wealth. They range from 378 points for students with no internet at -1

SD from the mean, to 451 for students with internet at +2 SD from the mean. All contrasts save for the one at level -2 SD wealth are significant. They range from 6 points for students at -1 SD wealth level to 14 points for students at +2 SD wealth level. Results across contrasts show that the greater the wealth, the greater the mean test score increase from internet access, though not to the same degree as for computer ownership.

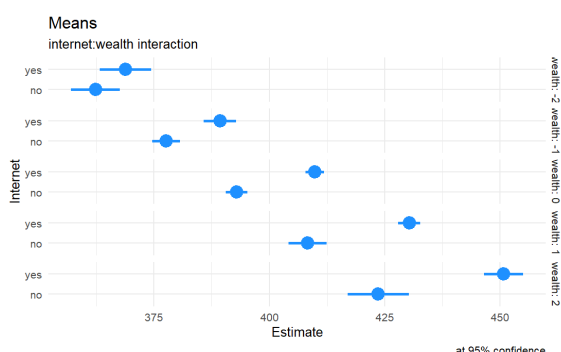


Figure 8 – Means, internet:wealth interaction

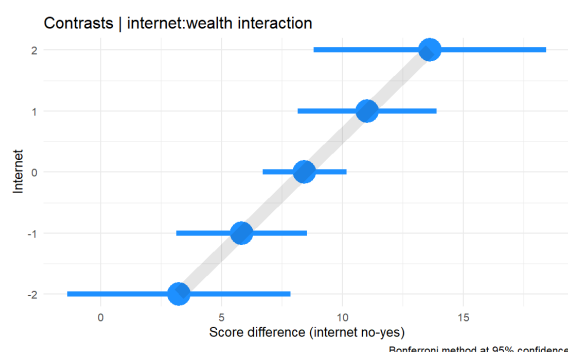


Figure 9 – Contrasts, internet:wealth interaction

Conclusion

Computer ownership and internet access have a statistically significant association with increased test scores across wealth levels, yielding an increase of 30 and 20 points in test scores, respectively, and 43 points combined, at mean wealth level. Below and above the mean wealth level, computer ownership and internet access test scores decrease/increase approximately by 11 and 5 points, respectively, for every unit of wealth, measured in standard deviations. Wealth alone impacts test scores by about plus/minus ten 10 points for every unit of wealth away from the mean.

A limitation of the study is the use of a composite math, reading and science test mean score, hiding the different impact of the factors under study on individual subject test performance. Another limitation is the absence of the student gender factor. A separate, preliminary analysis suggests that disaggregating test scores and factoring gender can strengthen further the analysis.

References

Kevin Wang, Paul Yacobellis, Erika Siregar, Sarah Romanes, Kim Fitter, Giulio Valentino, Dalla Riva, Dianne Cook, Nick Tierney, Priya Dingorkar; *learningtower: OECD PISA Datasets from 2000-2018 in an Easy-to-Use Format*; <https://github.com/kevinwang09/learningtower>

Appendix A - Data Summary Table

PISA_2018_Indonesia_Data

Dimensions: 11819 x 4

Duplicates: 0

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Valid	Missing
1	internet [factor]	1. no 2. yes	5545 (46.9%) 6274 (53.1%)		11819 (100.0%)	0 (0.0%)
2	computer [factor]	1. no 2. yes	6932 (58.7%) 4887 (41.3%)		11819 (100.0%)	0 (0.0%)
3	wealth [numeric]	Mean (sd) : 0 (1) min ≤ med ≤ max: -4.2 ≤ -0.1 ≤ 5.7 IQR (CV) : 1.2 (328.4)	3968 distinct values		11819 (100.0%)	0 (0.0%)
4	mean_TestScore [numeric]	Mean (sd) : 403.4 (75.4) min ≤ med ≤ max: 171.1 ≤ 397.1 ≤ 682.2 IQR (CV) : 105.5 (0.2)	11729 distinct values		11819 (100.0%)	0 (0.0%)

Appendix B – ANCOVA model table, means and contrasts

Model

<i>Predictors</i>	Dependent variable		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>
(Intercept)	378.13	375.35 – 380.90	< 0.001
computer [yes]	29.67	24.99 – 34.34	< 0.001
internet [yes]	20.29	16.50 – 24.08	< 0.001
wealth	9.84	7.26 – 12.42	< 0.001
computer [yes] * internet [yes]	-6.84	-13.07 – -0.62	0.031
computer [yes] * wealth	10.96	7.17 – 14.75	< 0.001
internet [yes] * wealth	5.19	1.36 – 9.02	0.008
Observations	11819		
R ² / R ² adjusted	0.195 / 0.195		

Model equation

$$\begin{aligned}
 \widehat{\text{mean_TestScore}} = & 378.13 \\
 & + 29.67(\text{computer}_{\text{yes}}) \\
 & + 20.29(\text{internet}_{\text{yes}}) \\
 & + 9.84(\text{wealth}) \\
 & - 6.84(\text{computer}_{\text{yes}} \times \text{internet}_{\text{yes}}) \\
 & + 10.96(\text{computer}_{\text{yes}} \times \text{wealth}) \\
 & + 5.19(\text{internet}_{\text{yes}} \times \text{wealth})
 \end{aligned}$$

ANOVA table

	Sum Sq	Df	F value	Pr(>F)
(Intercept)	327282540.74	1	71415.490	0.000
computer	709209.24	1	154.755	0.000
internet	503902.32	1	109.955	0.000
wealth	256133.43	1	55.890	0.000
computer:internet	21271.63	1	4.642	0.031
computer:wealth	147490.60	1	32.184	0.000
internet:wealth	32371.10	1	7.064	0.008
Residuals	54131972.83	11812		

Interaction effect *computer:internet*

Means

computer	internet	emmean	SE	df	lower.CL	upper.CL
no	no	378	1.42	11812	375	381
yes	no	408	1.92	11812	404	412
no	yes	398	1.32	11812	396	401
yes	yes	421	1.55	11812	418	424

Confidence level used: 0.95

Contrasts

contrast	estimate	SE	df	t.ratio	p.value
no no - yes no	-29.70	2.39	11812	-12.451	<.0001
no no - no yes	-20.31	1.94	11812	-10.486	<.0001
no no - yes yes	-43.16	2.04	11812	-21.150	<.0001
yes no - no yes	9.39	2.33	11812	4.038	0.0003
yes no - yes yes	-13.46	2.47	11812	-5.461	<.0001
no yes - yes yes	-22.85	2.04	11812	-11.217	<.0001

P value adjustment: bonferroni method for 6 tests

contrast	estimate	SE	df	lower.CL	upper.CL
no no - yes no	-29.70	2.39	11812	-35.99	-23.40
no no - no yes	-20.31	1.94	11812	-25.42	-15.20
no no - yes yes	-43.16	2.04	11812	-48.55	-37.78
yes no - no yes	9.39	2.33	11812	3.25	15.53
yes no - yes yes	-13.46	2.47	11812	-19.97	-6.96
no yes - yes yes	-22.85	2.04	11812	-28.23	-17.48

Confidence level used: 0.95

Conf-level adjustment: bonferroni method for 6 estimates

Appendix B (continued)

Interaction effect *computer:wealth*

Means

```
wealth = -2:
computer lsmean    SE    df lower.CL upper.CL
no       363.4  2.2398 11812   359.0   367.8
yes      367.7  3.3477 11812   361.2   374.3
```

```
wealth = -1:
computer lsmean    SE    df lower.CL upper.CL
no       375.8  1.2469 11812   373.4   378.3
yes      391.1  2.1192 11812   387.0   395.3
```

```
wealth = 0:
computer lsmean    SE    df lower.CL upper.CL
no       388.3  0.9667 11812   386.4   390.2
yes      414.5  1.2355 11812   412.1   416.9
```

```
wealth = 1:
computer lsmean    SE    df lower.CL upper.CL
no       400.7  1.7766 11812   397.2   404.2
yes      437.9  1.5212 11812   434.9   440.9
```

```
wealth = 2:
computer lsmean    SE    df lower.CL upper.CL
no       413.1  2.8670 11812   407.5   418.8
yes      461.3  2.6178 11812   456.2   466.4
```

Results are averaged over the levels of: internet
Confidence level used: 0.95

Contrasts

```
wealth = -2:
contrast estimate    SE    df t.ratio p.value
no effect    -2.16  2.144 11812   -1.008  0.6274
yes effect     2.16  2.144 11812    1.008  0.6274
```

```
wealth = -1:
contrast estimate    SE    df t.ratio p.value
no effect    -7.64  1.290 11812   -5.923 <.0001
yes effect     7.64  1.290 11812    5.923 <.0001
```

```
wealth = 0:
contrast estimate    SE    df t.ratio p.value
no effect   -13.12  0.774 11812  -16.944 <.0001
yes effect    13.12  0.774 11812   16.944 <.0001
```

```
wealth = 1:
contrast estimate    SE    df t.ratio p.value
no effect   -18.60  1.184 11812  -15.710 <.0001
yes effect    18.60  1.184 11812   15.710 <.0001
```

```
wealth = 2:
contrast estimate    SE    df t.ratio p.value
no effect   -24.08  2.018 11812  -11.936 <.0001
yes effect    24.08  2.018 11812   11.936 <.0001
```

Results are averaged over the levels of: internet
P value adjustment: bonferroni method for 2 tests

Interaction effect *internet:wealth*

Means

```
wealth = -2:
internet lsmean    SE    df lower.CL upper.CL
no       362.3  2.719 11812   357.0   367.6
yes      368.8  2.846 11812   363.2   374.4
```

```
wealth = -1:
internet lsmean    SE    df lower.CL upper.CL
no       377.6  1.551 11812   374.6   380.7
yes      389.3  1.797 11812   385.8   392.8
```

```
wealth = 0:
internet lsmean    SE    df lower.CL upper.CL
no       393.0  1.190 11812   390.6   395.3
yes      409.8  1.020 11812   407.8   411.8
```

```
wealth = 1:
internet lsmean    SE    df lower.CL upper.CL
no       408.3  2.102 11812   404.2   412.4
yes      430.3  1.237 11812   427.9   432.8
```

```
wealth = 2:
internet lsmean    SE    df lower.CL upper.CL
no       423.6  3.379 11812   417.0   430.2
yes      450.9  2.167 11812   446.6   455.1
```

Results are averaged over the levels of: computer
Confidence level used: 0.95

Contrasts

Results are averaged over the levels of: computer
Confidence level used: 0.95

```
wealth = -2:
contrast estimate    SE    df t.ratio p.value
no effect    -3.24  2.056 11812   -1.578  0.2292
yes effect     3.24  2.056 11812    1.578  0.2292
```

```
wealth = -1:
contrast estimate    SE    df t.ratio p.value
no effect    -5.84  1.208 11812   -4.833 <.0001
yes effect     5.84  1.208 11812    4.833 <.0001
```

```
wealth = 0:
contrast estimate    SE    df t.ratio p.value
no effect    -8.43  0.773 11812  -10.912 <.0001
yes effect     8.43  0.773 11812   10.912 <.0001
```

```
wealth = 1:
contrast estimate    SE    df t.ratio p.value
no effect   -11.03  1.281 11812   -8.608 <.0001
yes effect    11.03  1.281 11812    8.608 <.0001
```

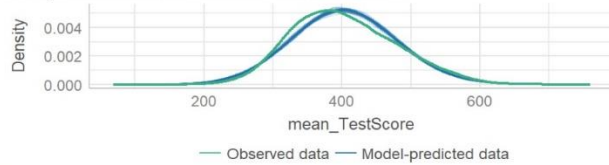
```
wealth = 2:
contrast estimate    SE    df t.ratio p.value
no effect   -13.62  2.143 11812   -6.357 <.0001
yes effect    13.62  2.143 11812    6.357 <.0001
```

Results are averaged over the levels of: computer
P value adjustment: bonferroni method for 2 tests

Appendix C – Model diagnostics

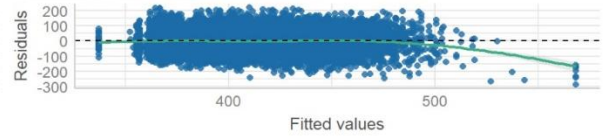
Posterior Predictive Check

Model-predicted lines should resemble observed data line



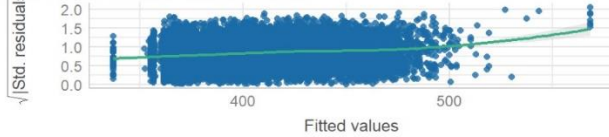
Linearity

Reference line should be flat and horizontal



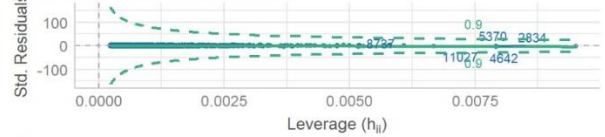
Homogeneity of Variance

Reference line should be flat and horizontal



Influential Observations

Points should be inside the contour lines



Collinearity

High collinearity (VIF) may inflate parameter uncertainty



Normality of Residuals

Points should fall along the line

