

# Mokoro - Tanzania

## 1 Data

**lgacontrols:** 89 variables ranging from population, poverty, government expenditure, data on educational system. Data ranges from 2015-2019. Not all data has complete series.

## 2 Payments

**payments\_alldrs:** 9 variables. Payments in dollars per DLI between 2015 and 2019, disaggregated at council level (LGA).

Between 184 and 185 LGA are eligible, although not all of them receive funds. Not all DLI are paid across range of years.

**payments\_alldlrs.c:** DLI payments are aggregated at council and DLI (losing time dimension) to use in the analysis of DLI 4 - PTR (only data on 2015 and 2019, a before/after).

About DLI 4.2: Average amount received: 82016\$, std. dev: 92569; 33 councils received 0. Quartiles: 1st: 14782, 3rd: 115000

DLI 4.2 over time: many councils with 0; year 2018 is the highest average: 33880, std. dev 65192. years 2016 and 2017 average lower: 16141, 11207, respectively.

Table 1: DLI payments per year - potential councils

	2016	2017	2018	2019
<b>2.2</b>	184	0	0	0
<b>2.3</b>	0	0	185	185
<b>3.2</b>	184	184	184	184
<b>4.2</b>	184	184	184	185
<b>7.1</b>	0	184	185	185
<b>7.2</b>	0	0	185	185
<b>8.2</b>	0	0	0	185

### DLI 4.2 payments per council

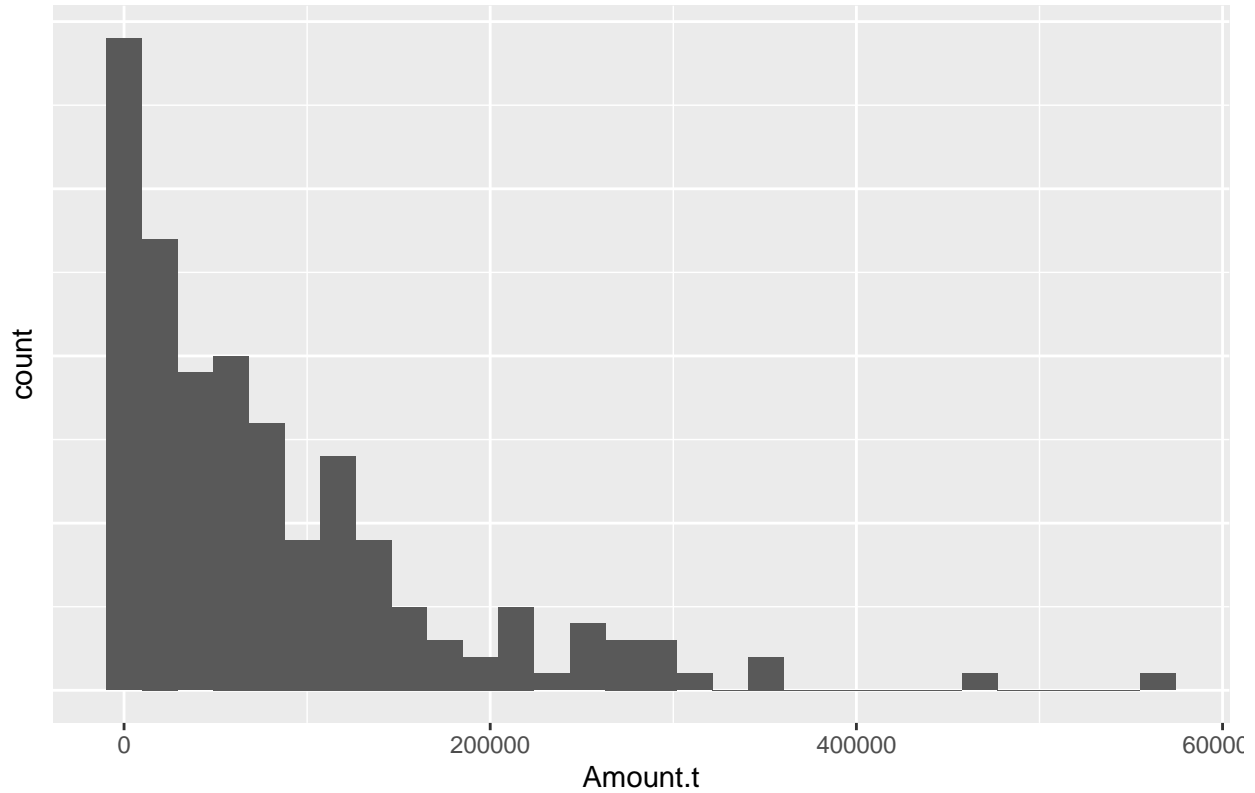


Table 2: Aggregated DLI 4.2 payments - Descriptive statistics

count	Mean.Amount.t	SD.Amount.t	Councils without receiveing
184	82016	92569	33

Table 3: DLI 4.2 payments per year - Descriptive statistics

Year	count	Mean.Amount	SD.Amount	Councils without receiveing
2016	184	16141	48358	131
2017	184	11207	29187	133
2018	184	33880	65192	82
2019	185	20676	47083	127

### 3 DLR 4 - Pupil teacher ratio

Pupil teacher ratio ranges from 0 to 884 studentes per teacher. This suggests measurement errors. Setting outliers at <1.5% and >98.5%, excluded values are <8.8 and > 113.82.

Table 4: PTR - Descriptive statistics

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
0	36.7	49.8	52.6	66.8	884	4

PTR is aggregated at LGA level because there is not match of 18172 of council/school names.

Analysing PTR over time (2015 and 2019), we observe median and mean are higher in the in 2019 roughly by 5.5 pupils.

Table 5: PTR by year without outliers - Descriptive statistics

year.ptr	Median.ptr.c	Mean.ptr.c	SD.ptr.c
2015	50.6	49.4	10.6
2019	56.1	54	12

This is explained by an important raise in students population (15.5% on average) and a smaller increase in teacher population (4.7%).

Total number of students per council across years

- **2015:**

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
9756	27763	45079	48421	61432	192743

- **2019:**

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
10524	32053	52079	55807	72915	226878

Total number of teachers per council across years

- **2015:**

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
161	617	916	1037	1231	5497

- **2019:**

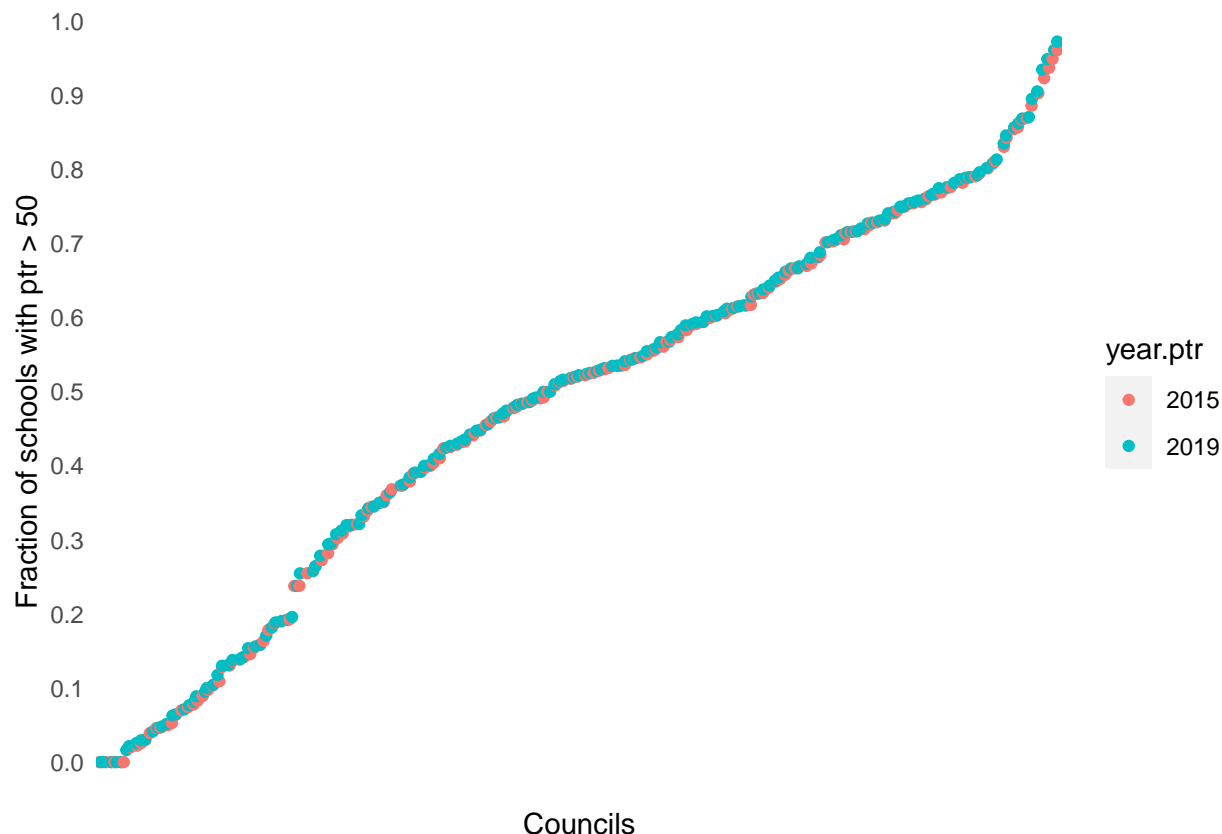
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
199	623	960	1086	1271	5936

School PTR across councils have deteriorated between 2015 and 2019. The overall average of schools with a PTR over 50 (which was the standard in 2015) growths from 42.1% to 54.4% and dispersion, measured by the standard deviation, also increases form 23.4% to 26.1%.

The following plot shows the fraction of schools above the acceptable threshold for 2015 (>50 students) in both years, ranging from 0 to 97.25%.

Table 10: Share of schools with PTR > 50 - Descriptive statistics

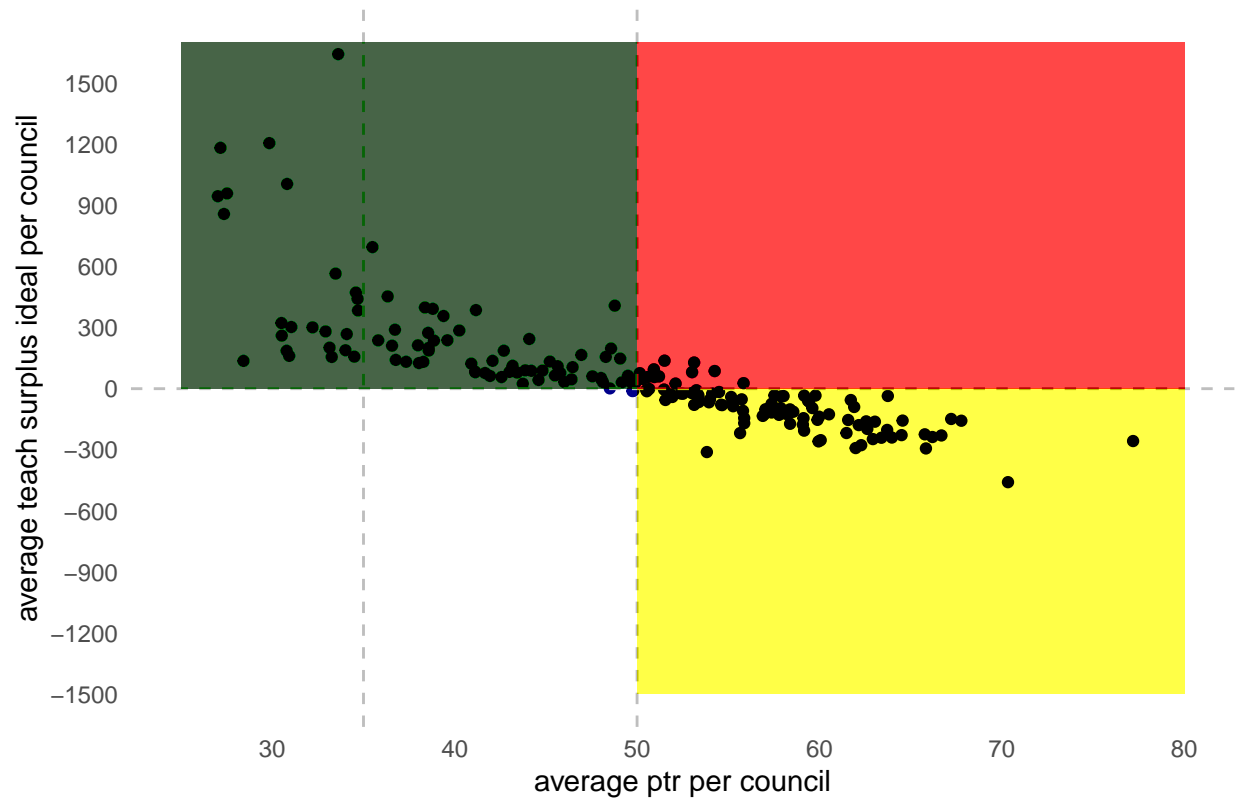
year.ptr	Median	Mean	SD
2015	0.476	0.421	0.234
2019	0.576	0.544	0.261



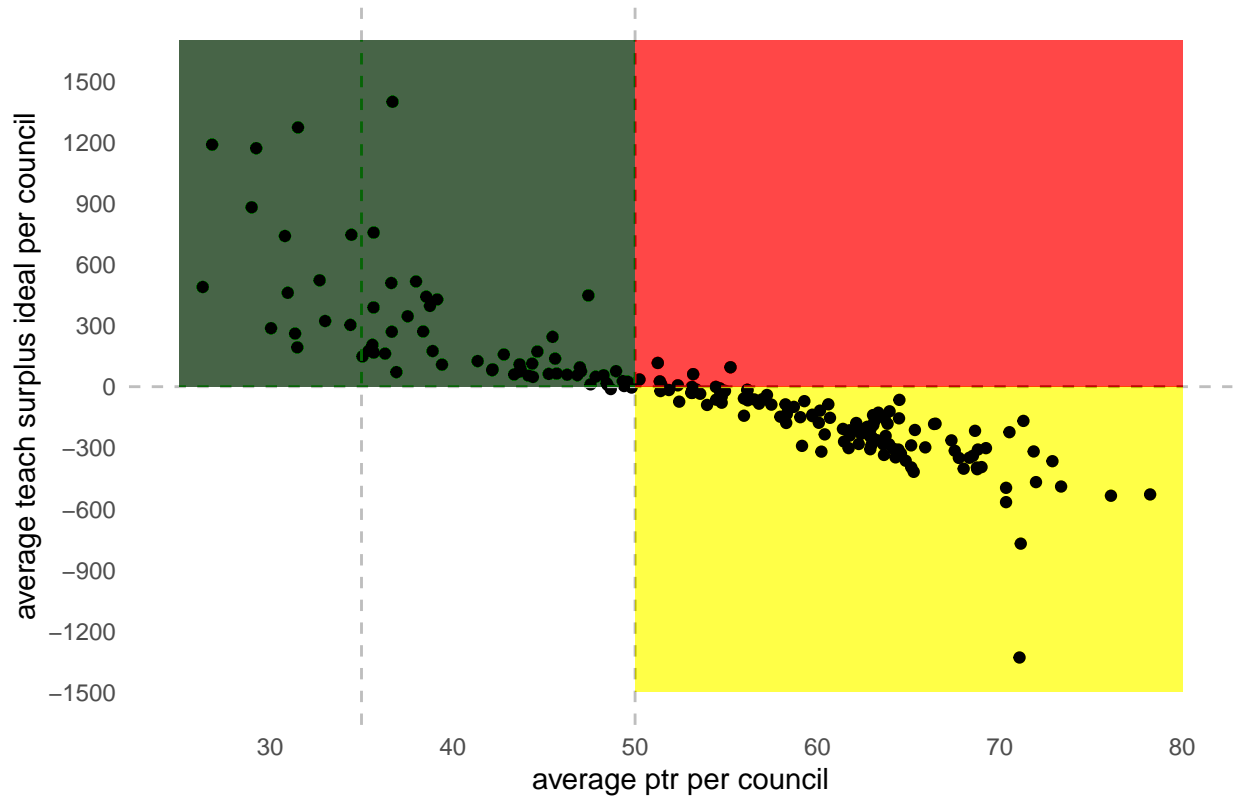
An ideal surplus of teachers per council was computed as  $\sum Teachers - (\sum Students/50)$ , which gives an idea of the ability of the council to achieve equity in the distribution of teachers. A major caveat of this calculation relies on the fact that students cannot follow the same ideal distribution due to household location, school resources and population age structure. However, this allows to understand the magnitude of gaps to be covered.

The following plots shows, for 2015 and 2019, the average PTR per council and the average ideal teacher surplus. The green area capture those councils under the PTR threshold, while the red are those which, having an ideal surplus, are above the PTR cutoff. The yellow area represents those councils that are both above PTR threshold and with teacher's deficit.

Average PTR and Ideal teacher surplus – 2015



Average PTR and Ideal teacher surplus – 2019



There is a strong negative linear correlation (-.79 and -.86) across both years. Both tails, in the negative and positive side, show different patterns.

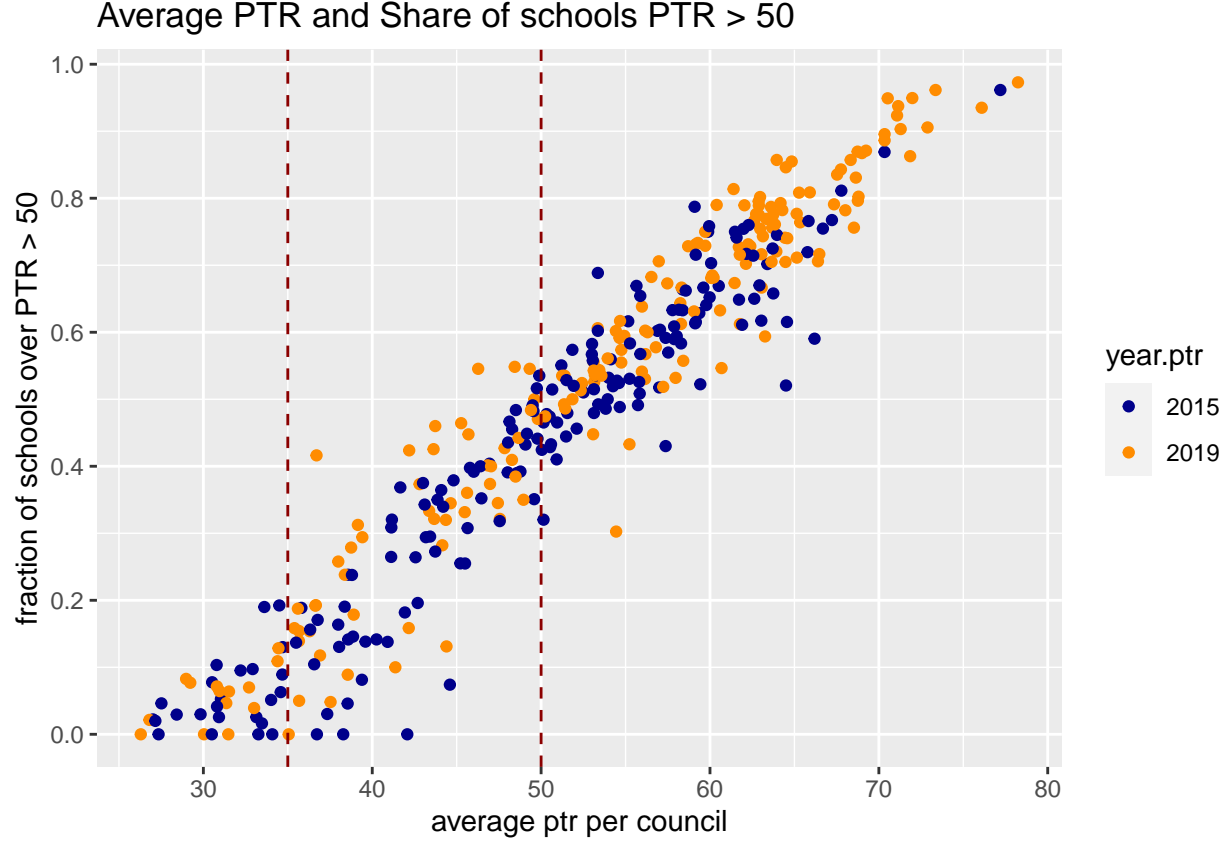
Table 11: Correlation PTR and teacher ideal distribution by council

year.ptr	cor
2015	-0.7943758
2019	-0.8583754

There is a very strong correlation between average PTR and share of schools with PTR above 50 per council, as shown in the following graph: .95 and .97 in 2015 and 2017.

Table 12: Correlation PTR and share of schools above PTR >50

year.ptr	cor
2015	0.9532881
2019	0.9662395



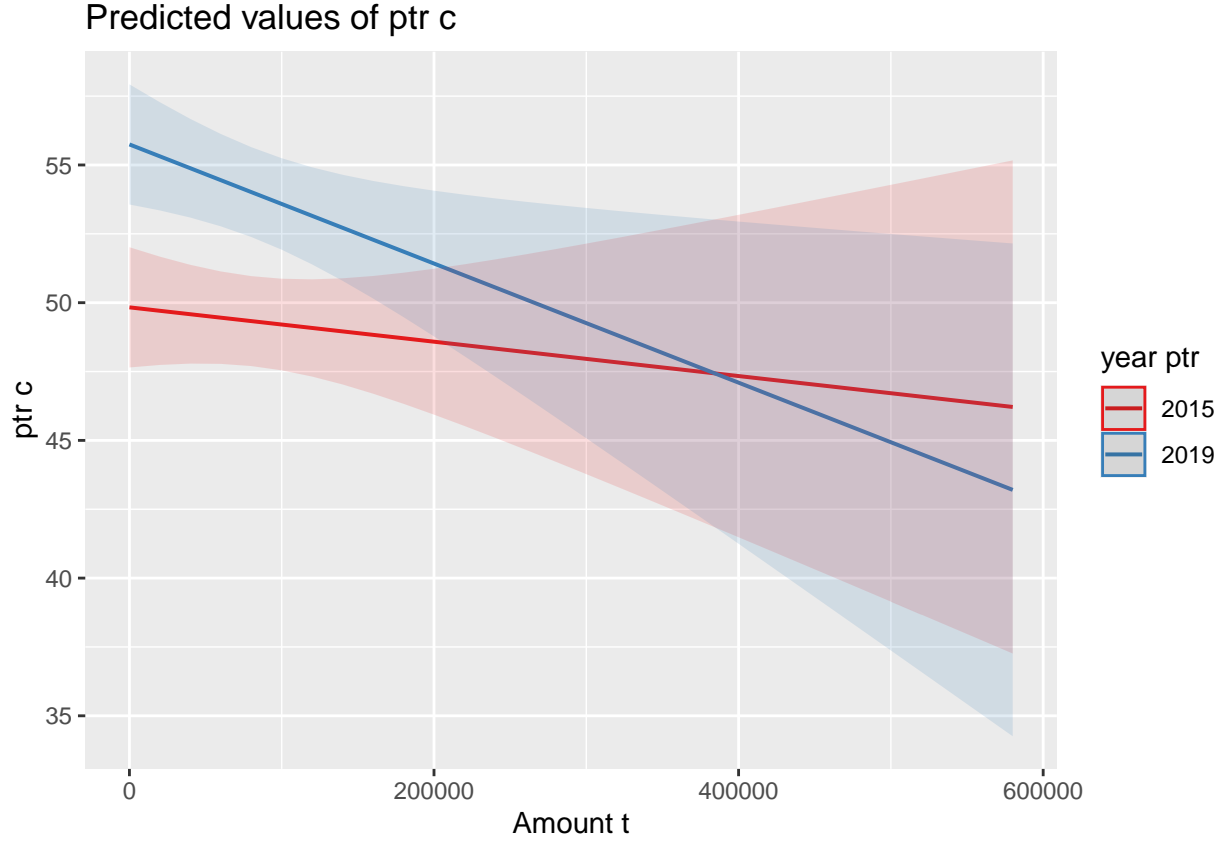
Turning to the analysis of PBR, we model a mixed-effects ANOVA to account for between- and within-council mean PTR differences. Only the year year and the interaction between year and DLI amount are significant. The relative magnitudes of the sums of squares indicates that the year term explains much more variation of PTR than the interaction term. Plotting the interaction predicted values we observe differences in terms of PTR across years when councils receive smaller values, which become insignificant later. To estimate differences, we use linear mixed-effects models, which are summarised below.

Table 13: Analysis of Variance - Type 3

	Sum Sq	Mean Sq	NumDF	DenDF	F value	Pr(>F)
<b>Amount.t</b>	27.3	27.3	1	182	2.5	0.116
<b>year.ptr</b>	27545	13772	2	180	1257	1.1e-106
<b>Amount.t:year.ptr</b>	185	185	1	179	16.9	0.0000611

Table 14: Model parameters

	Estimate	Std. Error	df	t value	Pr(> t )
<b>Amount.t</b>	-0.00000624	0.00000902	198	-0.691	0.49
<b>year.ptr2015</b>	49.8	1.11	199	44.7	1.19e-105
<b>year.ptr2019</b>	55.7	1.11	198	50.1	2.07e-114
<b>Amount.t:year.ptr2019</b>	-0.0000154	0.00000375	179	-4.11	0.0000611



We also normalise councils' received amounts by student, such as in  $amount/student$  and run the same ANOVA model. In this case, all terms, including the DLI amount, are significant, while the sum of squares suggest the year term is relatively higher in terms of explaining PTR. The  $amount/student$  estimate is significant and shows a negative sign, which suggests an association between  $amount/student$  and reducing PTR.

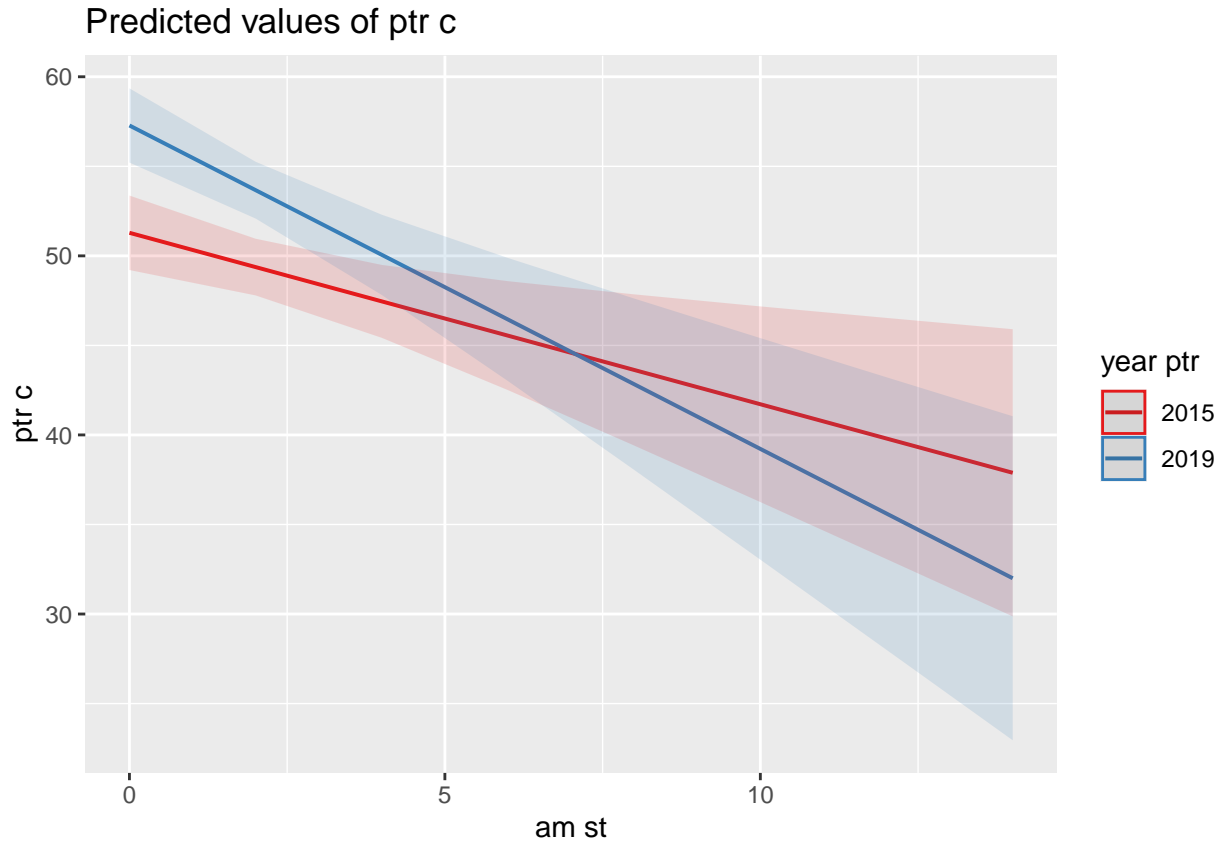
Table 15: Analysis of Variance - Type 3

	Sum Sq	Mean Sq	NumDF	DenDF	F value	Pr(>F)
<b>am.st</b>	170	170	1	202	15.9	0.000092
<b>year.ptr</b>	31416	15708	2	184	1469	5.42e-114
<b>am.st:year.ptr</b>	307	307	1	199	28.7	0.000000236

Table 16: Model parameters

	Estimate	Std. Error	df	t value	Pr(> t )
<b>am.st</b>	-0.957	0.336	220	-2.85	0.00476
<b>year.ptr2015</b>	51.3	1.06	208	48.3	5.27e-115
<b>year.ptr2019</b>	57.3	1.06	207	54.2	2.36e-124
<b>am.st:year.ptr2019</b>	-0.849	0.158	199	-5.35	0.000000236





## 4 DLR 6

### 4.1 National examns

Table 17: Correlation between # students and school score

exam	cor
PSLE	0.02908979
SFNA	-0.1479596

Table 18: Descriptive statistics - Ammount DLR

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
15527	44815	106906	134695	187638	851394	308

- 2014:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
NA	NA	NA	NA	NA	NA	154

- **2015:**

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
NA	NA	NA	NA	NA	NA	154

- **2016:**

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
16667	36062	36991	52187	41064	376393

- **2017:**

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
27206	51048	77206	98195	130236	324206

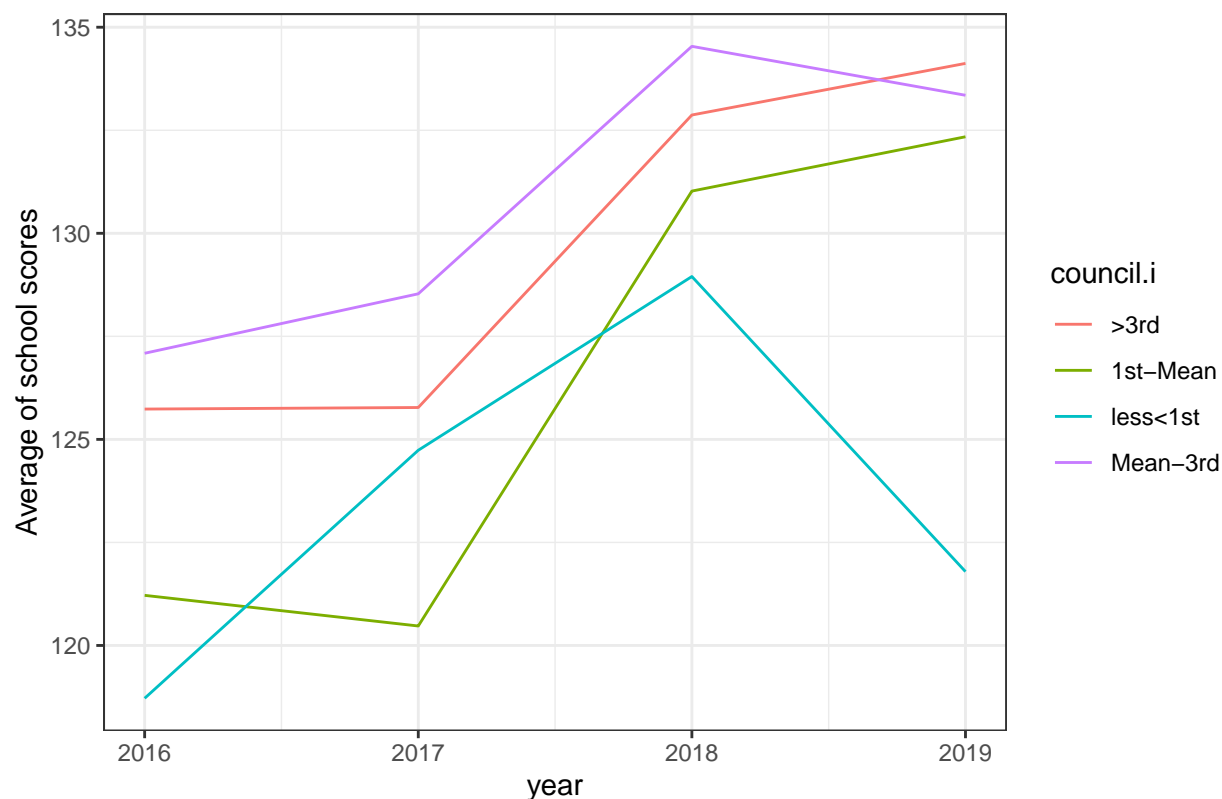
- **2018:**

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
15527	95789	139508	163823	204551	851394

- **2019:**

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
38168	140865	204447	224573	279948	791257

PSLE average of councils grouped by overall DLR received



Fixed effects models at council level - aggregating all money, considering learning outcomes (tests) as a impact.

```
## Twoways effects Within Model
##
## Call:
## plm(formula = score ~ am, data = nat.concil, effect = "twoways",
##      model = "within", index = c("council", "year"))
##
## Unbalanced Panel: n = 182, T = 1-4, N = 696
##
## Residuals:
##      Min.      1st Qu.      Median      3rd Qu.      Max.
## -30.017990  -3.091990  -0.023131   3.678247  26.410176
##
## Coefficients:
##      Estimate Std. Error t-value Pr(>|t|)
## am 0.0000114244 0.0000039912  2.8624 0.004377 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    29642
## Residual Sum of Squares: 29173
## R-Squared:    0.015811
## Adj. R-Squared: -0.3412
## F-statistic: 8.19327 on 1 and 510 DF, p-value: 0.0043775
```

```
##      Estimate Std. Error t-value Pr(>|t|)
## 2016 119.25281    0.62732  190.10 < 2.2e-16 ***
## 2017 122.32889    0.70491  173.54 < 2.2e-16 ***
## 2018 130.82457    0.86389  151.44 < 2.2e-16 ***
## 2019 131.37612    1.05566  124.45 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Random effects models at council level

```
## Twoways effects Random Effect Model
##      (Swamy-Arora's transformation)
##
## Call:
## plm(formula = score ~ am, data = nat.concil, effect = "twoways",
##      model = "random", index = c("council", "year"))
##
## Unbalanced Panel: n = 182, T = 1-4, N = 696
##
## Effects:
##              var std.dev share
## idiosyncratic 57.202   7.563 0.280
## individual    142.250  11.927 0.696
## time           4.849   2.202 0.024
## theta:
##      Min.   1st Qu.   Median     Mean   3rd Qu.     Max.
## id    0.4644675 0.6977630 0.6977630 0.6929966 0.6977630 0.6977630
## time  0.7416987 0.7445720 0.7520049 0.7480923 0.7532879 0.7532879
## total 0.4476793 0.6397208 0.6412462 0.6392554 0.6451080 0.6457621
##
## Residuals:
##      Min. 1st Qu.  Median     Mean 3rd Qu.     Max.
## -41.563 -10.154  -1.265   0.245   9.722  50.145
##
## Coefficients:
##              Estimate Std. Error z-value Pr(>|z|)
## (Intercept) 1.2558e+02 2.0246e-01  620.25 < 2.2e-16 ***
## am          1.3903e-05 4.9868e-07   27.88 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    162230
## Residual Sum of Squares: 155470
## R-Squared:    0.067199
## Adj. R-Squared: 0.065855
## Chisq: 30.1907 on 1 DF, p-value: 3.9159e-08
##
##      gamma      nu
## 0.9502553 0.9778201
```

Random effects models adding covariates (in lme4 - more flexible) - models don't converge

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
```

```

## lmerModLmerTest]
## Formula:
## score ~ am + year + pop2019 + urbrur + povertyregion + dropout_uw2015_pct +
##      (1 + year | council)
##      Data: nat.concil
##
## REML criterion at convergence: 4401.6
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.7584 -0.4798 -0.0133  0.5248  3.3484
##
## Random effects:
##      Groups   Name                Variance  Std.Dev. Corr
##      council  (Intercept)  64.66400169  8.041393
##              year          0.00003413  0.005842 -0.53
##      Residual                64.75501883  8.047050
## Number of obs: 582, groups:  council, 152
##
## Fixed effects:
##              Estimate Std. Error      df t value    Pr(>|t|)
## (Intercept)   -9.501e+03  7.840e+02  4.588e+02 -12.120    < 2e-16 ***
## am              8.550e-06  4.379e-06  5.023e+02  1.953    0.051427 .
## year           4.768e+00  3.888e-01  4.588e+02  12.265    < 2e-16 ***
## pop2019        1.443e-05  3.910e-06  1.472e+02  3.691    0.000313 ***
## urbrurUrban    1.029e+01  2.168e+00  1.491e+02  4.749  0.00000476 ***
## povertyregion  4.447e+00  1.290e+01  1.505e+02  0.345    0.730811
## dropout_uw2015_pct -1.927e-01  4.999e-01  1.474e+02 -0.385    0.700436
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) am      year  pp2019 urbrurU pvrtyr
## am              0.630
## year            -1.000 -0.630
## pop2019          -0.033 -0.047  0.031
## urbrurUrban     0.012  0.016 -0.012 -0.044
## povertyreg      0.008  0.015 -0.011  0.211 -0.067
## drpt_w2015_    -0.005 -0.015  0.005 -0.088  0.245 -0.534
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling
## convergence code: 0
## unable to evaluate scaled gradient
## Model failed to converge: degenerate Hessian with 2 negative eigenvalues

```