V4 Lab Main Report

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Introduction

This is the main technical report of the V4 Lab Project. Its aim is twofold: 1) to see what is the level of economic/financial knowledge of Polish and Czech students and what are their attitudes in regard to economic liberalism/interventionism; 2) to answer the main research problem posed in this project, that is whether there is a relationship between economic and financial knowledge, liberal/interventionist attitudes and type of obtained education (EBMF, SSHA and STEM). Moreover we also check potential connections between knowledge and attitudes and some sociodemographics such as parental education and work experience.

We estimate level of the economic/financial knowledge by three means: 1) we investigate answer patterns to separate items (i.e. which are most diffcult etc.); 2) analyze what we call raw scores, that is sums of correct answers; 3) analyze what we call non-guessed answers, that is the number of correct answers that were not guessed. The last measure is based on an assumption that since the items were of true/false form then in the case when one does not know the correct answer the problem of answering such an item boils down to guessing with 50% chance of a hit. Under this assumption it is easy to derive the number of questions that must have been answered correctly in a nonrandom fashion (that is respondent must have been quite certain that the answer he or she gives is the correct one). The number of correct answers may be computed using the following formula: $C = 2X - 2E$, where C is the score, X is the actual number of correct answers given and E is the expected number of such answers (in this case this is a constant that equals 14.5, since there are 29 items with guessing chance of 50%).

Furthermore, KNOWLEDGE items of true/false form give us one more opportunity - it is easy to partition the item set into three subsets: 1) easy items (those with difficulty significantly below 0.5, what implies that on average respondents do know the correct answer and there is no need for guessing); 2) medium items (those around difficulty level of 0.5, what implies that on average respondents do not know the answer for sure and guess); 3) tricky items (those with difficulty significantly above 0.5, what implies that on average respondents have false beliefs about them).

Liberal/interventionist economic attitudes are measured using the liberalism-interventionism preferential scale that we constructed for the purpose of this project (more information about the scale can be found in the dedicated report). This scale ranges from -8 to 8 and negative scores correspond to the liberal pole of it and positive to the interventionist one (the in-sample range is a bit narrower and spans from -7 to 7). However, the extreme values of -8 and 8 are not detectable in practice for some technical reasons which we will not discuss here. This problem is not important because no respondents have answer patterns that would lead to this kind of complication.

Parental education is assessed on the basis of three variables. The first two of them are father and mother education. These are categorical variables with four levels: 1) vocational education or lower; 2) high school; 3) higher education (defiend as BA or MA or equivalent); 4) PHD and above. The levels are slightly different from the original answer categories available in the questionnaire we used, where they were more detailed. This is due to the fact that some answers were very rare and we needed to group them into wider categories.

The third variable we use to asses parental education is based on the previous ones. We call it the Ordinal Indicator of Joint Parental Education (OIJPE). It is constructed as follows: 1) recode father and mother education to integers ranging from 0 to 3 in such a manner that it preserves the education levels order; 2) add the recoded variables (it creates a variable ranging from 0 to 6). Of course (as the name suggests) OIJPE should not be treated as an interval or rational variable, but only as an ordinal one.

In the end we would like to introduce technical labels for some of the main variables that may appear throught the output tables in this report:

- **libsoc:** interventionism-interventionism scale
- **ngknow:** Non-guessed knowledge score
- **knowraw:** Knowledge raw score
- **peduord:** Ordinal Indicator of the Joint Parental Education (OIJPE)

Descriptive statistics for knowledge and attitudes

Below we provide numerical summaries for the liberalism-interventionism scale and the raw and non-guessed knowledge scores in terms of mean and positional parameters (quartiles and deciles).

Descriptives for the Joint Sample

Mean and quartiles

```
##      libsoc            ngknow          knowraw
##  Min.   :-7.0000   Min.   :-14.000   Min.   : 8.00
##  1st Qu.:-1.0000   1st Qu.:  0.000   1st Qu.:15.00
##  Median : 1.0000   Median :  6.000   Median :18.00
##  Mean   : 0.3964   Mean   :  5.746   Mean   :17.87
##  3rd Qu.: 2.0000   3rd Qu.: 10.000   3rd Qu.:20.00
##  Max.   : 7.0000   Max.   : 22.000   Max.   :26.00
##  NA's   :22        NA's   :57        NA's   :57
```

Deciles

```
## $libsoc
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##   -7   -3   -2   -1    0    1    1    2    2    3    7
##
## $ngknow
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##  -14   -4    0    2    4    6    8   10   12   14   22
##
## $knowraw
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##    8   13   15   16   17   18   19   20   21   22   26
```

Descriptives by country

Mean and quartiles

```
## $libsoc
## $libsoc$CZ
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
## -5.0000 -1.0000  1.0000  0.6832  2.0000  6.0000       7
##
## $libsoc$PL
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
## -7.0000 -2.0000  1.0000  0.1067  2.0000  7.0000      15
##
```

```
##
## $ngknow
## $ngknow$CZ
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   -10.0     2.0     6.0     5.8    10.0    18.0      30
##
## $ngknow$PL
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
## -14.000   0.000   6.000   5.694  12.000  22.000      27
##
##
## $knowraw
## $knowraw$CZ
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    10.0    16.0    18.0    17.9    20.0    24.0      30
##
## $knowraw$PL
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    8.00   15.00   18.00   17.85   21.00   26.00      27
```

Deciles

```
## $libsoc
## $libsoc$CZ
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##   -5   -2   -1   -1    0    1    1    2    3    3    6
##
## $libsoc$PL
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##   -7   -3   -2   -1    0    1    1    1    2    3    7
##
##
## $ngknow
## $ngknow$CZ
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##  -10   -2    0    2    4    6    8   10   12   14   18
##
## $ngknow$PL
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##  -14   -4   -2    2    4    6    8   10   12   16   22
##
##
## $knowraw
## $knowraw$CZ
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##   10   14   15   16   17   18   19   20   21   22   24
##
## $knowraw$PL
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##    8   13   14   16   17   18   19   20   21   23   26
```

Descriptives by education type (EBMF, SSHA and STEM)

Mean and quartiles

```
## $libsoc
## $libsoc$EBMF
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
## -7.0000 -2.0000 -1.0000 -0.2487  1.0000  7.0000       5 
## 
## $libsoc$SSHA
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   -5.00    0.00    1.00    1.04    3.00    6.00       9 
## 
## $libsoc$STEM
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
## -5.0000 -1.0000  1.0000  0.2416  2.0000  6.0000       6 
## 
## 
## $ngknow
## $ngknow$EBMF
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   -8.00    6.00   10.00    9.76   14.00   22.00       6 
## 
## $ngknow$SSHA
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
## -14.000  -2.000   2.000   2.793   8.000  18.000      18 
## 
## $ngknow$STEM
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##  -8.000   0.000   6.000   5.111  10.000  22.000      31 
## 
## 
## $knowraw
## $knowraw$EBMF
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   11.00   18.00   20.00   19.88   22.00   26.00       6 
## 
## $knowraw$SSHA
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##     8.0    14.0    16.0    16.4    19.0    24.0      18 
## 
## $knowraw$STEM
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   11.00   15.00   18.00   17.56   20.00   26.00      31
```

Deciles

```
## $libsoc
## $libsoc$EBMF
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100% 
##   -7   -3   -3   -2   -1   -1    1    1    2    3    7 
## 
## $libsoc$SSHA
```

```
##    0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##    -5   -2   -1    0    1    1    2    2    3    3    6
##
## $libsoc$STEM
##    0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##    -5   -3   -2   -1    0    1    1    1    2    3    6
##
##
## $ngknow
## $ngknow$EBMF
##    0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
## -8.0  2.0  4.4  6.0  8.8 10.0 12.0 14.0 14.0 16.0 22.0
##
## $ngknow$SSHA
##    0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##   -14   -6   -2    0    2    2    4    6    8   10   18
##
## $ngknow$STEM
##    0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##    -8   -2    0    2    4    6    6    8   10   12   22
##
##
## $knowraw
## $knowraw$EBMF
##    0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
## 11.0 16.0 17.2 18.0 19.4 20.0 21.0 22.0 22.0 23.0 26.0
##
## $knowraw$SSHA
##    0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##     8   12   14   15   16   16   17   18   19   20   24
##
## $knowraw$STEM
##    0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##    11   14   15   16   17   18   18   19   20   21   26
```

Descriptives by education type and country

Mean and quartiles

```
## $libsoc
## $libsoc$EBMF.CZ
##      Min.  1st Qu.   Median     Mean  3rd Qu.     Max.     NA's
## -4.00000 -2.00000  0.00000 -0.03125  2.00000  6.00000        1
##
## $libsoc$SSHA.CZ
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -3.000   0.000   1.000   1.014   2.500   6.000       5
##
## $libsoc$STEM.CZ
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -5.000  -0.250   1.000   1.017   3.000   5.000       1
##
## $libsoc$EBMF.PL
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
## -7.0000 -2.0000 -1.0000 -0.4639  1.0000  7.0000       4 
## 
## $libsoc$SSHA.PL
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##  -5.000   0.000   1.000   1.089   3.000   4.000       4 
## 
## $libsoc$STEM.PL
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
## -5.0000 -2.0000  0.0000 -0.1525  1.0000  6.0000       5 
## 
## 
## $ngknow
## $ngknow$EBMF.CZ
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   -8.00    6.00   10.00    8.43   12.00   18.00       4 
## 
## $ngknow$SSHA.CZ
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
## -10.000   0.000   4.000   3.515   8.000  16.000      16 
## 
## $ngknow$STEM.CZ
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##  -6.000   4.000   6.000   7.098  12.000  18.000      10 
## 
## $ngknow$EBMF.PL
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   -8.00    8.00   12.00   11.01   16.00   22.00       2 
## 
## $ngknow$SSHA.PL
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##  -14.00   -4.00    2.00    1.58    6.00   18.00       2 
## 
## $ngknow$STEM.PL
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##  -8.000   0.000   4.000   4.118   8.000  22.000      21 
## 
## 
## $knowraw
## $knowraw$EBMF.CZ
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   11.00   18.00   20.00   19.22   21.00   24.00       4 
## 
## $knowraw$SSHA.CZ
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   10.00   15.00   17.00   16.76   19.00   23.00      16 
## 
## $knowraw$STEM.CZ
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   12.00   17.00   18.00   18.55   21.00   24.00      10 
## 
## $knowraw$EBMF.PL
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   11.00   19.00   21.00   20.51   23.00   26.00       2 
```

```
##
## $knowraw$SSHA.PL
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    8.00   13.00   16.00   15.79   18.00   24.00       2
##
## $knowraw$STEM.PL
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   11.00   15.00   17.00   17.06   19.00   26.00      21
```

Deciles

```
## $libsoc
## $libsoc$EBMF.CZ
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##   -4   -3   -2   -2   -1    0    1    1    2    3    6
##
## $libsoc$SSHA.CZ
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##   -3   -1   -1    0    1    1    1    2    3    3    6
##
## $libsoc$STEM.CZ
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##   -5   -2   -1    0    1    1    2    2    3    3    5
##
## $libsoc$EBMF.PL
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
## -7.0 -3.4 -3.0 -2.0 -1.0 -1.0  0.0  1.0  2.0  3.0  7.0
##
## $libsoc$SSHA.PL
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
## -5.0 -2.0 -0.4  1.0  1.0  1.0  2.0  2.0  3.0  3.0  4.0
##
## $libsoc$STEM.PL
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##   -5   -3   -3   -1   -1    0    1    1    2    3    6
##
##
## $ngknow
## $ngknow$EBMF.CZ
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##   -8    2    4    6    6   10   10   12   14   14   18
##
## $ngknow$SSHA.CZ
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##  -10   -4   -2    0    2    4    6    6    8   10   16
##
## $ngknow$STEM.CZ
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##   -6    0    4    4    6    6    8   10   12   14   18
##
## $ngknow$EBMF.PL
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
## -8.0  2.0  6.0  8.0 10.0 12.0 12.0 14.0 16.0 18.4 22.0
```

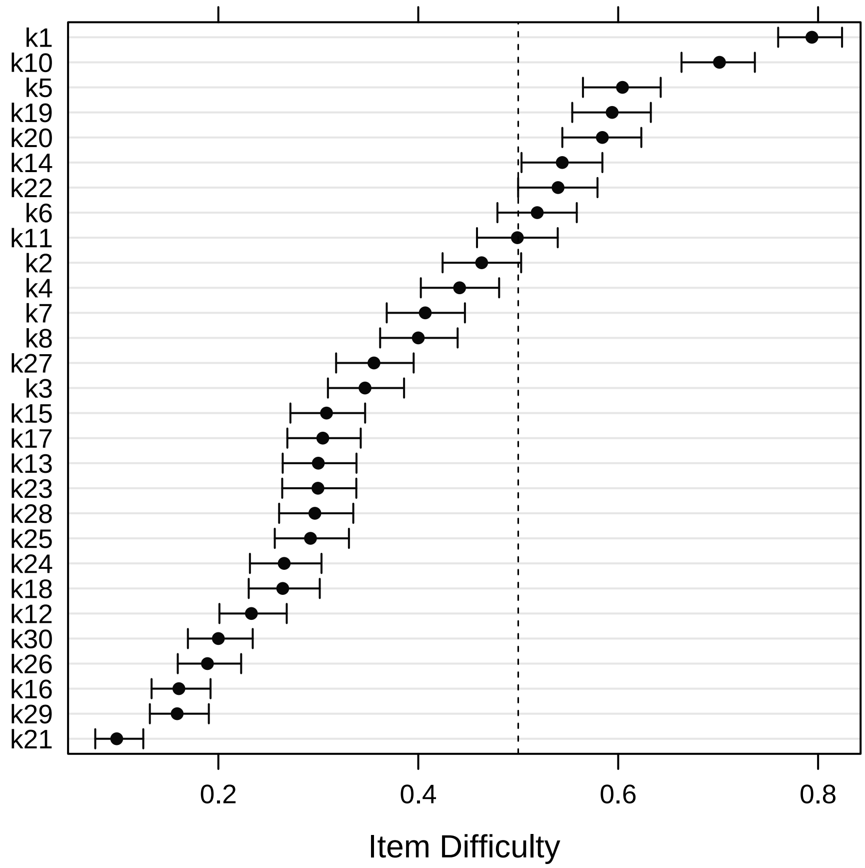
```
##
## $ngknow$SSHA.PL
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##  -14   -8   -4   -2    0    2    4    4    8   10   18
##
## $ngknow$STEM.PL
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##   -8   -4   -2    0    2    4    6    8   10   12   22
##
##
## $knowraw
## $knowraw$EBMF.CZ
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##   11   16   17   18   18   20   20   21   22   22   24
##
## $knowraw$SSHA.CZ
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##   10   13   14   15   16   17   18   18   19   20   23
##
## $knowraw$STEM.CZ
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##   12   15   17   17   18   18   19   20   21   22   24
##
## $knowraw$EBMF.PL
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
## 11.0 16.0 18.0 19.0 20.0 21.0 21.0 22.0 23.0 24.2 26.0
##
## $knowraw$SSHA.PL
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##    8   11   13   14   15   16   17   17   19   20   24
##
## $knowraw$STEM.PL
##   0%  10%  20%  30%  40%  50%  60%  70%  80%  90% 100%
##   11   13   14   15   16   17   18   19   20   21   26
```

Analysis of the KNOWLEDGE items set

Now we turn to the analysis of the KNOWLEDGE items set. We will partition it into subsets of easy, medium and tricky items and check whether items orderings in regard to difficulty levels are the same in different subgroups.

For this purpose we will inspect numerical values of difficulty levels (difficulty of an item is of course the fraction of respondents giving the incorrect answer) and visualize this data using dotplots with 95% Agresti-Coul confidence intervals.

KNOWLEDGE items set in the Joint Sample



We see from the plot that items may be partitioned (according to our rule) in the following way:

```
## $tricky
## [1] "k1"  "k10" "k5"  "k19" "k20" "k14" "k22"
##
## $medium
## [1] "k6"  "k11" "k2"
##
## $easy
##  [1] "k4"  "k7"  "k8"  "k27" "k3"  "k15" "k17" "k13" "k23" "k28" "k25"
## [12] "k24" "k18" "k12" "k30" "k26" "k16" "k29" "k21"
```

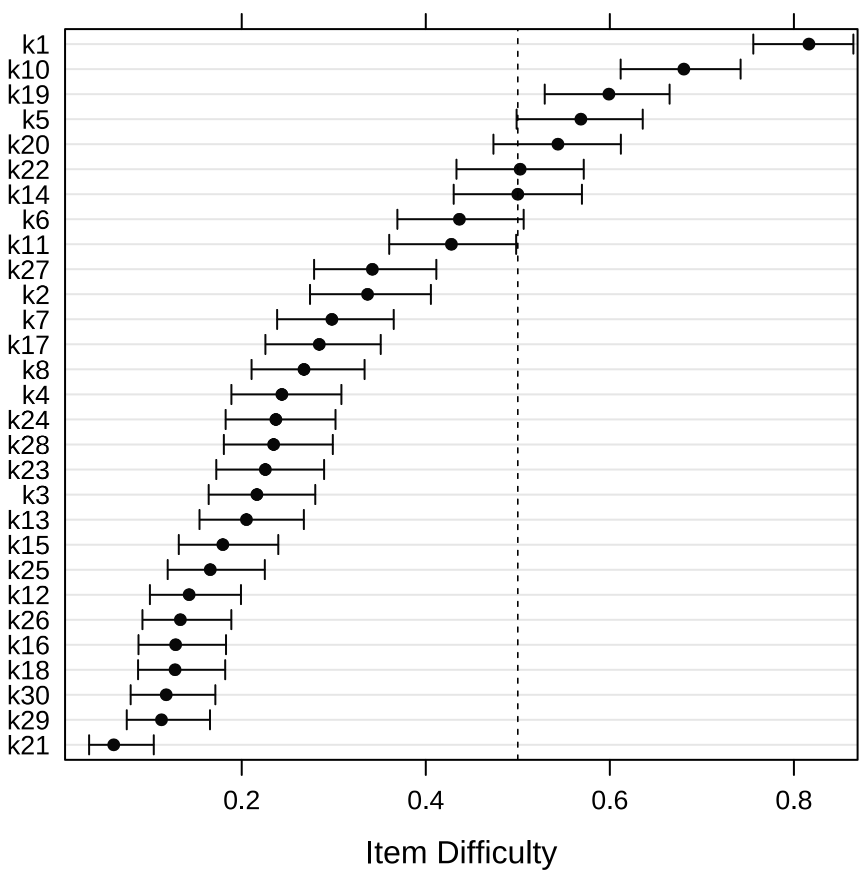
Below we provide numerical values for the difficulties and their confidence intervals:

```
##     difficulty lower upper
## k1       0.206 0.176 0.240
## k2       0.537 0.497 0.576
## k3       0.653 0.614 0.690
## k4       0.559 0.519 0.597
## k5       0.396 0.357 0.435
## k6       0.481 0.441 0.521
## k7       0.593 0.553 0.632
## k8       0.600 0.561 0.638
```

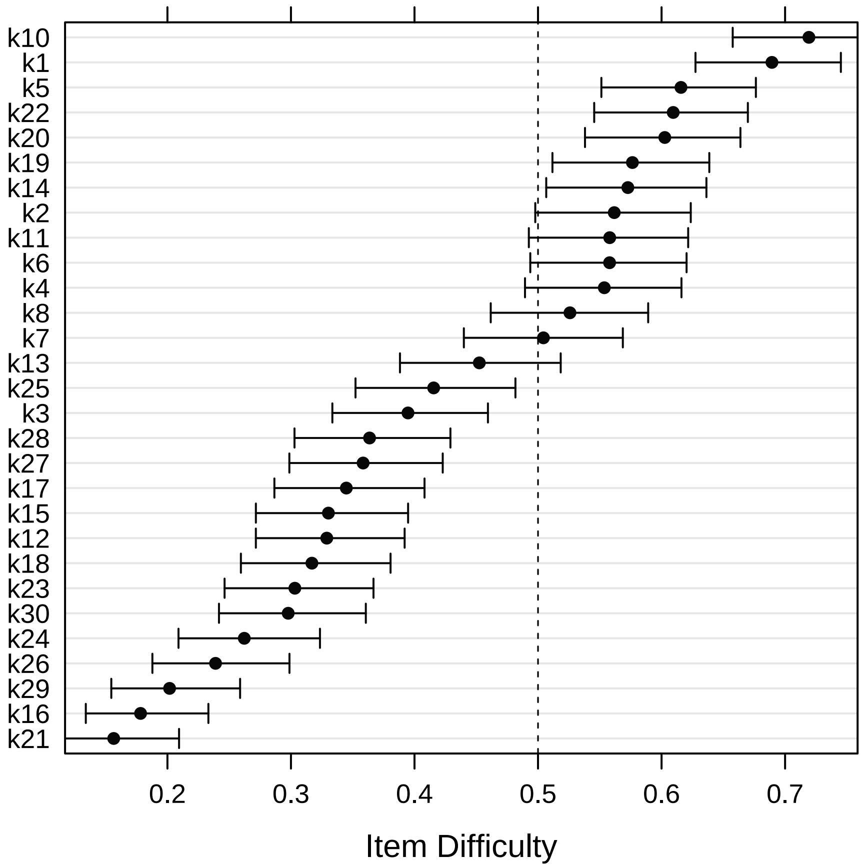
```
## k10      0.299 0.263 0.337
## k11      0.501 0.460 0.541
## k12      0.767 0.732 0.799
## k13      0.700 0.662 0.736
## k14      0.456 0.416 0.497
## k15      0.692 0.653 0.728
## k16      0.839 0.808 0.867
## k17      0.696 0.658 0.731
## k18      0.736 0.699 0.770
## k19      0.406 0.367 0.446
## k20      0.416 0.377 0.456
## k21      0.902 0.875 0.923
## k22      0.460 0.421 0.500
## k23      0.700 0.662 0.736
## k24      0.734 0.697 0.768
## k25      0.708 0.669 0.744
## k26      0.811 0.777 0.841
## k27      0.644 0.605 0.682
## k28      0.703 0.665 0.739
## k29      0.841 0.810 0.869
## k30      0.800 0.766 0.830
```

Knowledge scores and type of education

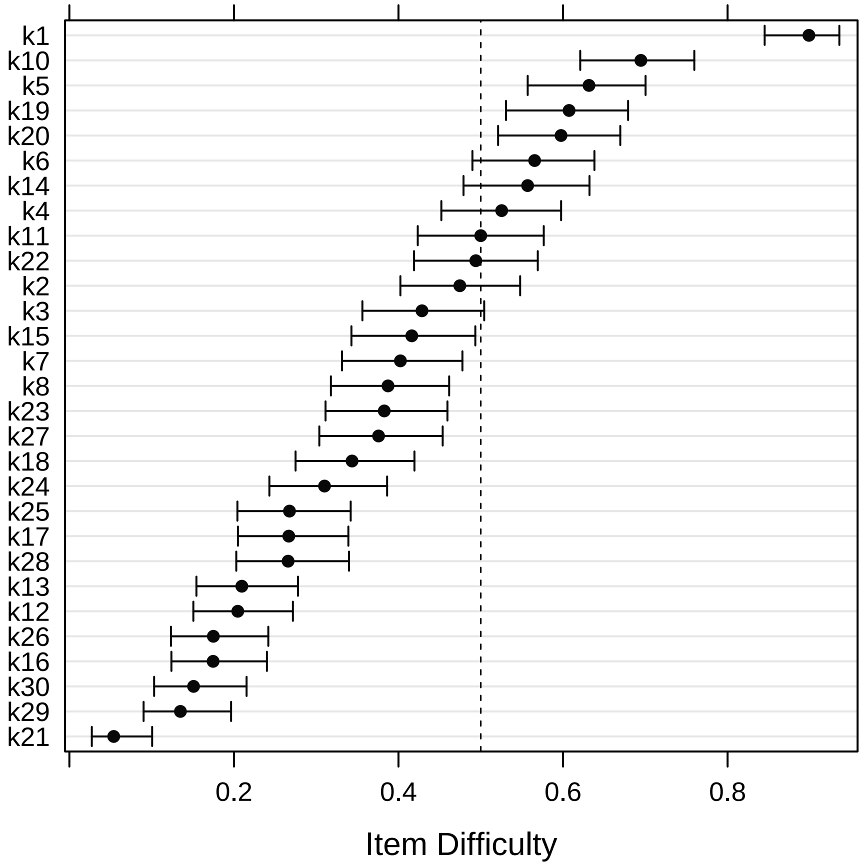
EBMF students



SSHA students

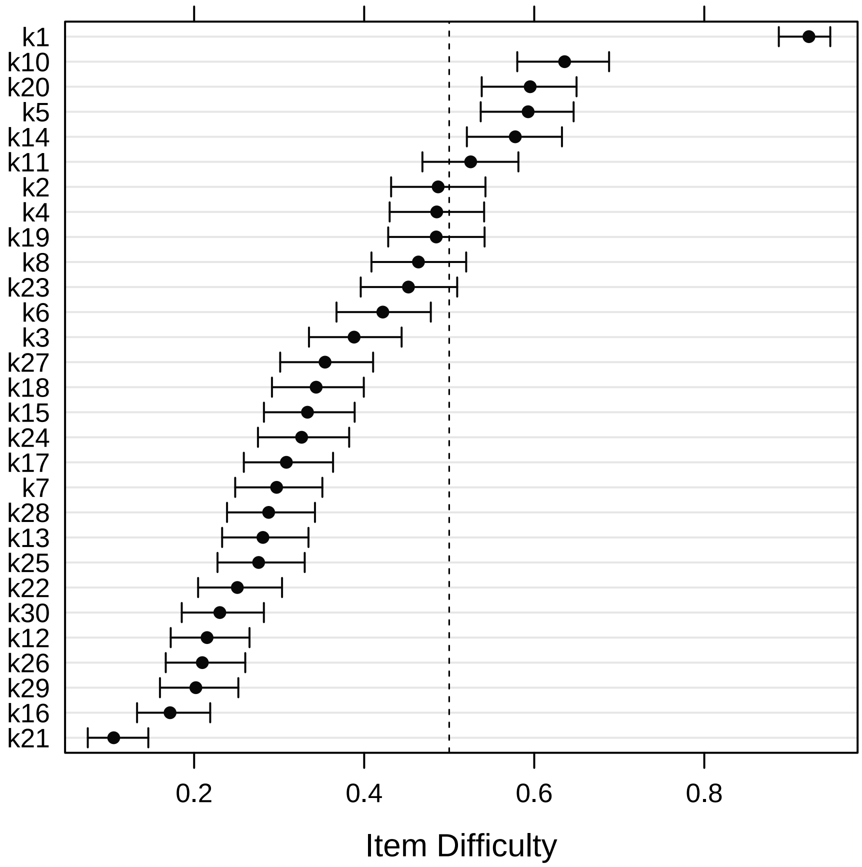


STEM students



Knowledge scores and country

Polish students



We see from the plot that items may be partitioned (according to our rule) in the following way:

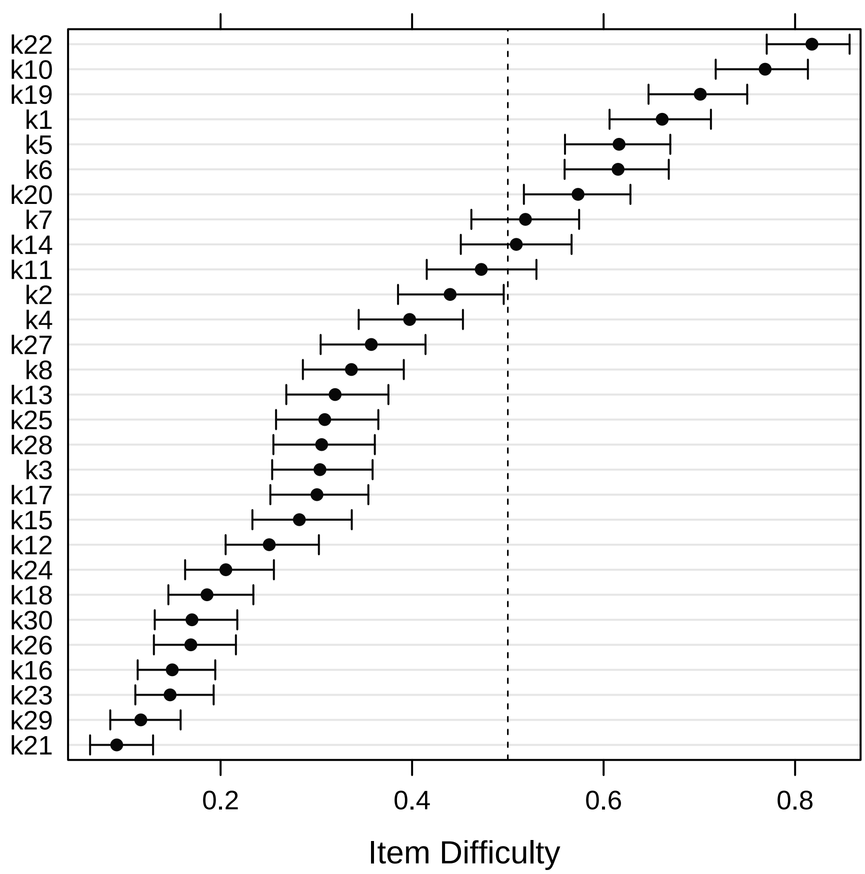
```
## $tricky
## [1] "k1"  "k10" "k20" "k5"  "k14"
##
## $medium
## [1] "k11" "k2"  "k4"  "k19" "k8"  "k23"
##
## $easy
##  [1] "k6"  "k3"  "k27" "k18" "k15" "k24" "k17" "k7"  "k28" "k13" "k25"
## [12] "k22" "k30" "k12" "k26" "k29" "k16" "k21"
```

Below we provide numerical values for the difficulties and their confidence intervals:

```
##     difficulty lower upper
## k1       0.077 0.052 0.112
## k2       0.513 0.457 0.568
## k3       0.612 0.556 0.665
## k4       0.515 0.459 0.570
## k5       0.407 0.354 0.463
## k6       0.578 0.522 0.633
```

```
## k7        0.703 0.649 0.752
## k8        0.536 0.480 0.591
## k10       0.364 0.312 0.420
## k11       0.475 0.419 0.531
## k12       0.785 0.735 0.828
## k13       0.719 0.666 0.767
## k14       0.422 0.367 0.479
## k15       0.667 0.611 0.718
## k16       0.828 0.781 0.867
## k17       0.692 0.637 0.742
## k18       0.656 0.600 0.708
## k19       0.515 0.458 0.572
## k20       0.405 0.350 0.462
## k21       0.895 0.854 0.925
## k22       0.749 0.697 0.795
## k23       0.548 0.491 0.604
## k24       0.674 0.618 0.725
## k25       0.724 0.670 0.772
## k26       0.790 0.740 0.833
## k27       0.646 0.589 0.699
## k28       0.712 0.658 0.761
## k29       0.798 0.748 0.840
## k30       0.770 0.718 0.815
```

Czech students



We see from the plot that items may be partitioned (according to our rule) in the following way:

```
## $tricky
## [1] "k22" "k10" "k19" "k1"  "k5"  "k6"  "k20"
##
## $medium
## [1] "k7"  "k14" "k11"
##
## $easy
##  [1] "k2"  "k4"  "k27" "k8"  "k13" "k25" "k28" "k3"  "k17" "k15" "k12"
## [12] "k24" "k18" "k30" "k26" "k16" "k23" "k29" "k21"
```

Below we provide numerical values for the difficulties and their confidence intervals:

```
##     difficulty lower upper
## k1       0.339 0.288 0.394
## k2       0.560 0.504 0.615
## k3       0.696 0.641 0.746
## k4       0.603 0.547 0.656
## k5       0.384 0.330 0.440
## k6       0.385 0.332 0.441
## k7       0.482 0.426 0.538
## k8       0.663 0.609 0.714
## k10      0.231 0.187 0.283
## k11      0.528 0.470 0.585
## k12      0.749 0.697 0.795
## k13      0.680 0.625 0.731
## k14      0.491 0.433 0.549
## k15      0.718 0.663 0.767
## k16      0.850 0.806 0.887
## k17      0.699 0.646 0.748
## k18      0.814 0.766 0.855
## k19      0.299 0.250 0.353
## k20      0.427 0.372 0.483
## k21      0.908 0.871 0.936
## k22      0.182 0.143 0.230
## k23      0.853 0.807 0.889
## k24      0.795 0.744 0.837
## k25      0.691 0.635 0.742
## k26      0.831 0.784 0.870
## k27      0.643 0.586 0.696
## k28      0.694 0.639 0.745
## k29      0.883 0.842 0.915
## k30      0.830 0.783 0.869
```

Before moving to the next part of the analysis it would be good to compare items partitioning in the Joint Sample and Polish and Czech samples.

```
## Joint Sample
```

```
## $tricky
## [1] "k1"  "k10" "k5"  "k19" "k20" "k14" "k22"
```

```
##
## $medium
## [1] "k6"  "k11" "k2"
##
## $easy
##  [1] "k4"  "k7"  "k8"  "k27" "k3"  "k15" "k17" "k13" "k23" "k28" "k25"
## [12] "k24" "k18" "k12" "k30" "k26" "k16" "k29" "k21"
```

```
## PL Sample
```

```
## $tricky
## [1] "k1"  "k10" "k20" "k5"  "k14"
##
## $medium
## [1] "k11" "k2"  "k4"  "k19" "k8"  "k23"
##
## $easy
##  [1] "k6"  "k3"  "k27" "k18" "k15" "k24" "k17" "k7"  "k28" "k13" "k25"
## [12] "k22" "k30" "k12" "k26" "k29" "k16" "k21"
```

```
## CZ Sample
```

```
## $tricky
## [1] "k22" "k10" "k19" "k1"  "k5"  "k6"  "k20"
##
## $medium
## [1] "k7"  "k14" "k11"
##
## $easy
##  [1] "k2"  "k4"  "k27" "k8"  "k13" "k25" "k28" "k3"  "k17" "k15" "k12"
## [12] "k24" "k18" "k30" "k26" "k16" "k23" "k29" "k21"
```

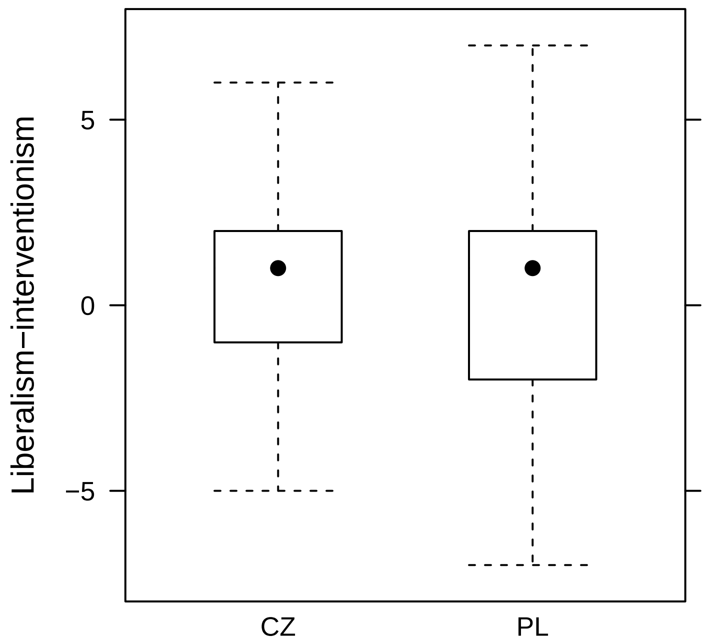
Clearly some items do overlap in different groups, but not all of them.

Associations analysis

In this section we will examine various associations between knowledge scores and the liberalism-interventionism axis as well as parental education, work experience and type of education.

Liberalism-interventionism amongst Polish and Czech students

We begin with an analysis of the differences in regard to the liberalism-interventionism scale scores between Polish and Czech students. We see that the distributions are slightly different - the Polish one is more spread out and shifted a bit more in the direction of liberalism; however both have means above zero, that is on the 'interventionist' side of the scale.




```
##   country libsoc.mean libsoc.sd
## 1      CZ   0.6831683  2.152762
## 2      PL   0.1066667  2.369389
```

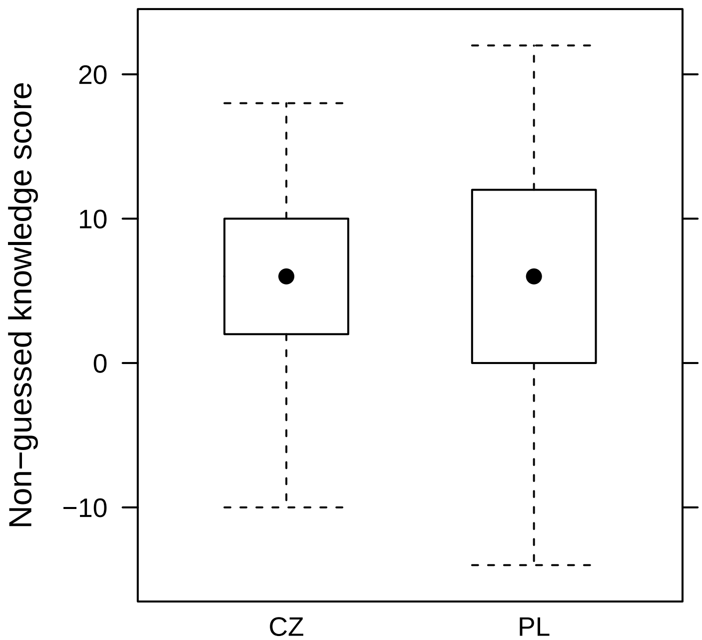
Formal test show that indeed Polish students are closer to the midpoint of the scale, while Czechs gravitate more to the side of interventionism. Although the effect is significant its magnitude is rather small (as Cohen's *d* coefficients shows).

```
##
##  Welch Two Sample t-test
##
## data:  libsoc by country
## t = 3.1261, df = 594.38, p-value = 0.001858
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.2143203 0.9386830
## sample estimates:
## mean in group CZ mean in group PL
##        0.6831683        0.1066667
```

```
##
## Cohen's d
##
## d estimate: 0.2547366 (small)
## 95 percent confidence interval:
##        inf        sup
## 0.09386418 0.41560912
```

Knowledge scores in the Polish and Czech samples

In this case distributions are very similar (since non-guessed score is a function of raw score we show charts only for the non-guessed).




```
##   country ngknow.mean knowraw.mean ngknow.sd knowraw.sd
## 1      CZ    5.800000     17.90000  5.973898   2.986949
## 2      PL    5.694444     17.84722  7.644795   3.822398
```

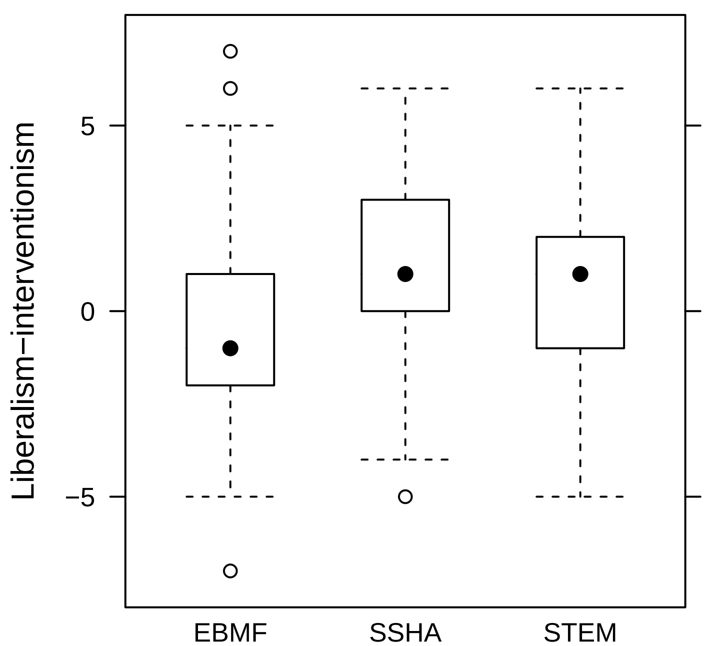
Formal tests also prove that there is no significant difference in this regard between the samples.

```
## $ngknow
##
##  Welch Two Sample t-test
##
## data:  x by data$country
## t = 0.18364, df = 541.14, p-value = 0.8544
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -1.023535  1.234646
## sample estimates:
## mean in group CZ mean in group PL
##         5.800000         5.694444
##
##
## $knowraw
##
##  Welch Two Sample t-test
##
## data:  x by data$country
## t = 0.18364, df = 541.14, p-value = 0.8544
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.5117673  0.6173229
## sample estimates:
## mean in group CZ mean in group PL
##         17.90000         17.84722
```

```
## $ngknow
##
## Cohen's d
##
## d estimate: 0.01535998 (negligible)
## 95 percent confidence interval:
##        inf        sup
## -0.1497788  0.1804988
##
## $knowraw
##
## Cohen's d
##
## d estimate: 0.01535998 (negligible)
## 95 percent confidence interval:
##        inf        sup
## -0.1497788  0.1804988
```

Liberalism-interventionism and education type

Now we compare education type groups (EBMF, SSHA and STEM) in a context of the liberalism-Socailism scale scores. It is easy to see that EBMF group is shifted towards liberalism, while SSHA tends to have stronger interventionist attitudes. The STEM group is between and closie to the midpoint.



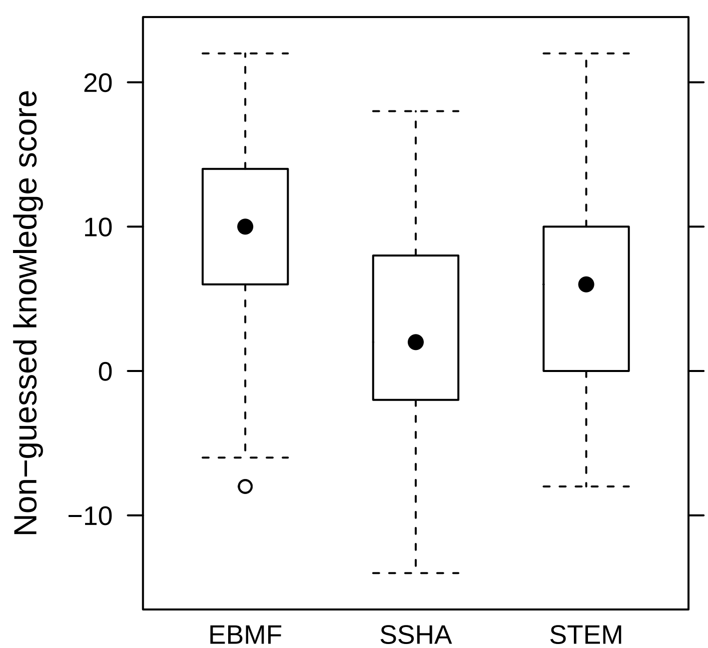

```
##   eduprog3 libsoc.mean libsoc.sd
## 1     EBMF  -0.2487047  2.455926
## 2     SSHA   1.0398230  1.921390
## 3     STEM   0.2415730  2.310150
```

A formal test (ANOVA) shows that education type matters and that about 5.7% of the variance of the liberalism-interventionism scale scores is associated with it. Moreover EBMF mean is not significantly greater than 0 (the scale's midpoint) and both STEM and SSHA groups have higher (more interventionist) means than it - although this effect is stronger in the SSHA group.

```
##
## Call:
## lm(formula = libsoc ~ eduprog3, data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.7513 -1.7513 -0.0398  1.7584  7.2487
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -0.2487     0.1600  -1.555   0.1205
## eduprog3SSHA   1.2885     0.2178   5.916 5.57e-09 ***
## eduprog3STEM   0.4903     0.2309   2.123   0.0342 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.222 on 594 degrees of freedom
##   (28 observations deleted due to missingness)
## Multiple R-squared:  0.05723,    Adjusted R-squared:  0.05406
## F-statistic: 18.03 on 2 and 594 DF,  p-value: 2.501e-08
```

Knowledge scores and education type

Without a doubt the EBMF group have much higher scores. On average EBMF students gave almost 10 correct answers without guessing while STEM students gave about 5 and SSHA students below 3.




```
##   eduprog3 ngknow.mean knowraw.mean ngknow.sd knowraw.sd
## 1     EBMF    9.760417     19.88021  6.187718   3.093859
```

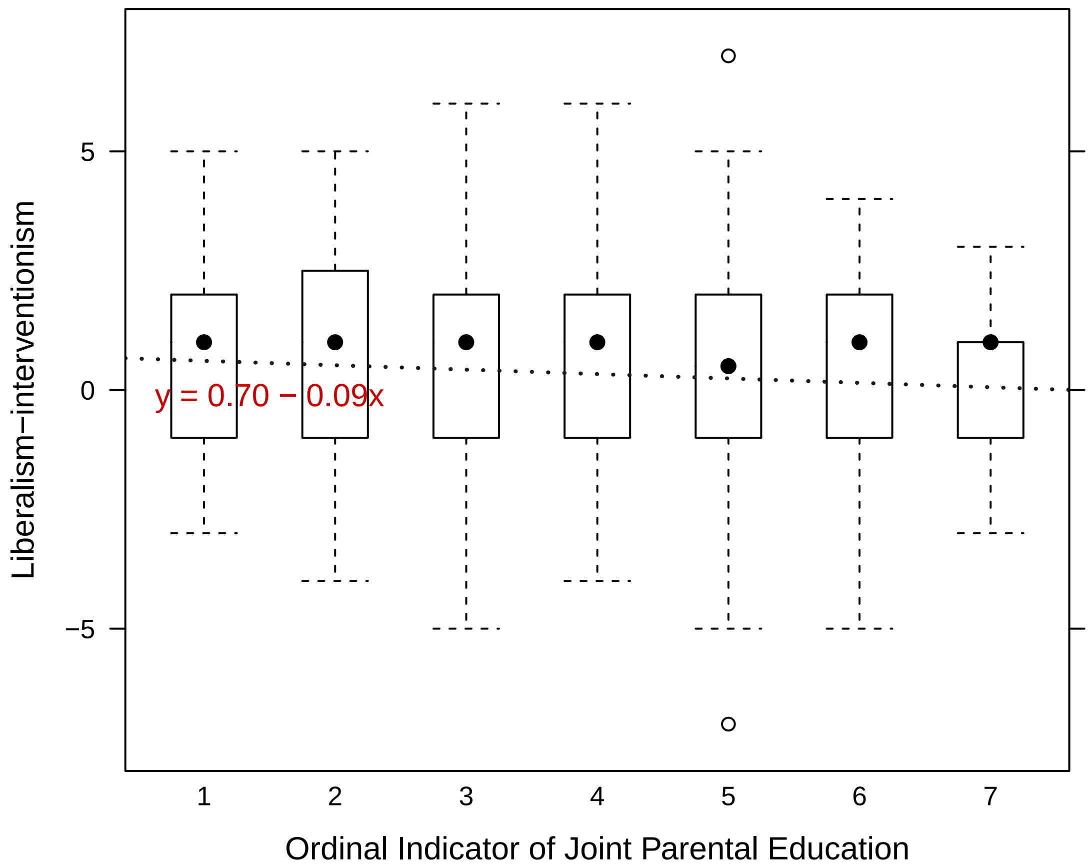
```
## 2     SSHA    2.792627     16.39631  6.149250   3.074625
## 3     STEM    5.111111     17.55556  6.047570   3.023785
```

19.3% of variance of the knowledge scores is associated with the effect of education type and both STEM and SSHA groups have significanly lower means than the EBMF group.

```
##
## Call:
## lm(formula = ngknow ~ eduprog3, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -17.7604  -3.7604   0.8889   4.2396  16.8889
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    9.7604     0.4428  22.045  < 2e-16 ***
## eduprog3SSHA  -6.9678     0.6078 -11.463  < 2e-16 ***
## eduprog3STEM  -4.6493     0.6649  -6.993 7.71e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.135 on 559 degrees of freedom
##   (63 observations deleted due to missingness)
## Multiple R-squared:  0.1935, Adjusted R-squared:  0.1906
## F-statistic: 67.04 on 2 and 559 DF,  p-value: < 2.2e-16
```

Liberalism-interventionism and OIJPE

Numerical values show that there is some variation in the group means, however it is hard to say whether it is something more than noise. The line on the plot depicts the linear regression model that tries to predict group means assuming that the relationship between the liberalism-interventionism scale scores nad the OIJPE values is close to linear.




```
##   peduord libsoc.mean libsoc.sd
## 1       0   0.6250000  2.226732
## 2       1   0.6323529  2.284957
## 3       2   0.3962264  2.105228
## 4       3   0.6899225  2.221340
## 5       4   0.2241379  2.373089
## 6       5   0.2142857  2.484875
## 7       6   0.1764706  1.740521
```

A formal test shows that there is no significant relationship between the liberalism-interventionism scale scores and the OIJPE scores.

```
##
## Call:
## lm(formula = libsoc ~ peduord, data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7.3341 -1.5184  0.4816  1.6429  6.6659
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.70271    0.21109   3.329 0.000929 ***
## peduord     -0.09216    0.06600  -1.396 0.163135
## ---
```

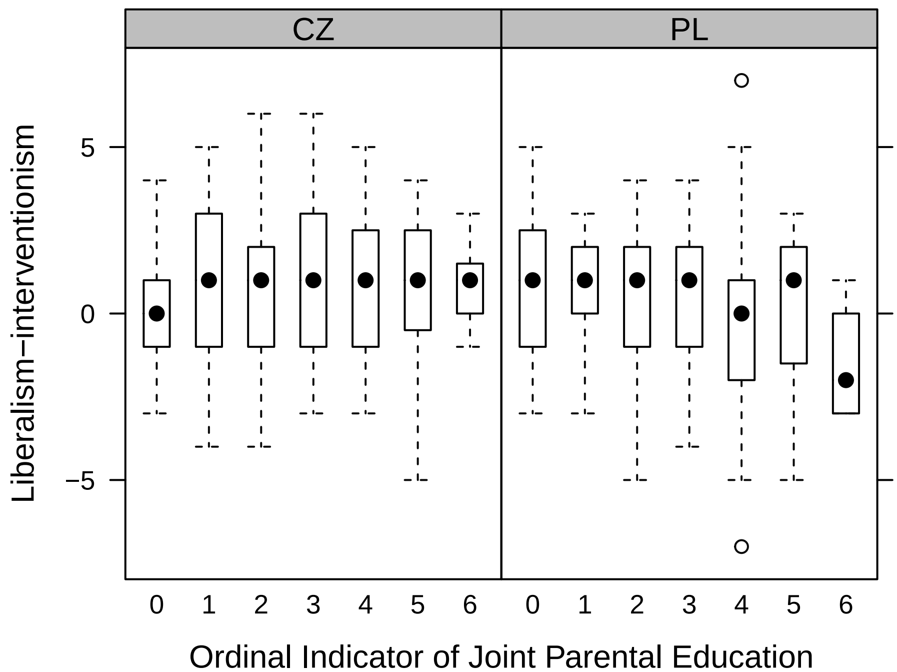
```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.253 on 560 degrees of freedom
##   (63 observations deleted due to missingness)
## Multiple R-squared:  0.00347,    Adjusted R-squared:  0.001691
## F-statistic:  1.95 on 1 and 560 DF,  p-value: 0.1631
```

Liberalism-interventionism and OIJPE by country

Additionaly we checked whether the association between the OIJPE scores and liberalism-interventionism varies between the countries. Distributions conditioned on country show that interventionist attitudes are more or less constant amongst Czech students but falling with parental education amongst Polish students.

```
## $`0.CZ`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -3.0000 -1.0000  0.0000  0.4118  1.0000  4.0000
##
## $`1.CZ`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
## -4.0000 -1.0000  1.0000  0.5581  3.0000  5.0000       1
##
## $`2.CZ`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
## -4.0000 -1.0000  1.0000  0.4906  2.0000  6.0000       1
##
## $`3.CZ`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
## -3.0000 -1.0000  1.0000  0.8519  3.0000  6.0000       2
##
## $`4.CZ`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -3.000  -1.000   1.000   0.875   2.250   5.000       1
##
## $`5.CZ`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
## -5.0000 -0.2500  1.0000  0.5833  2.2500  4.0000       1
##
## $`6.CZ`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -1.0000  0.5000  1.0000  0.8333  1.2500  3.0000
##
## $`0.PL`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -3.0000 -1.0000  1.0000  0.7826  2.5000  5.0000
##
## $`1.PL`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   -3.00    0.00    1.00    0.76    2.00    3.00       2
##
## $`2.PL`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
## -5.0000 -1.0000  1.0000  0.3019  2.0000  4.0000       2
##
```

```
## $`3.PL`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
## -4.0000 -1.0000  1.0000  0.4167  2.0000  4.0000       2
##
## $`4.PL`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
## -7.0000 -2.0000  0.0000 -0.3298  1.0000  7.0000       6
##
## $`5.PL`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
## -5.0000 -1.2500  1.0000 -0.0625  2.0000  3.0000       1
##
## $`6.PL`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    -3.0    -3.0    -2.0    -1.4     0.0     1.0
```



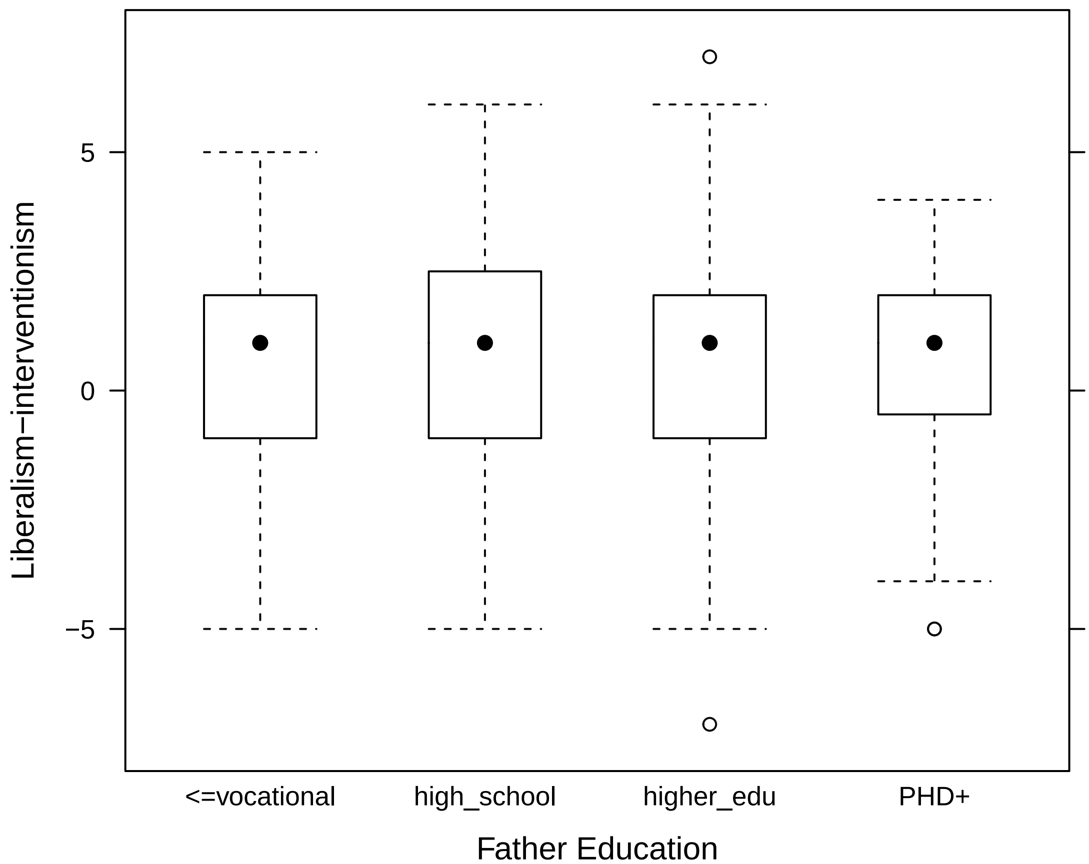
Formal test (linear model with OIJPE × country interaction) proves the observation. Polish students' attitudes tend to be more liberal when parents have higher education.

```
##
## Call:
## lm(formula = libsoc ~ peduord * country, data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.8131 -1.6395  0.2701  1.4693  7.1869
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)          0.45877    0.28628   1.603  0.10960
## peduord              0.09039    0.09029   1.001  0.31722
```

```
## countryPL          0.48428    0.41713   1.161  0.24614
## peduord:countryPL -0.37286    0.13030  -2.862  0.00437 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.222 on 558 degrees of freedom
##   (63 observations deleted due to missingness)
## Multiple R-squared:  0.03423,    Adjusted R-squared:  0.02904
## F-statistic: 6.593 on 3 and 558 DF,  p-value: 0.0002202
```

Liberalism-interventionism and father education

Distributions in the groups suggest no strong association.




```
##     father_edu libsoc.mean libsoc.sd
## 1 <=vocational   0.4628099  2.232492
## 2  high_school   0.5945946  2.212635
## 3   higher_edu   0.3067729  2.307708
## 4         PHD+   0.5813953  2.162809
```

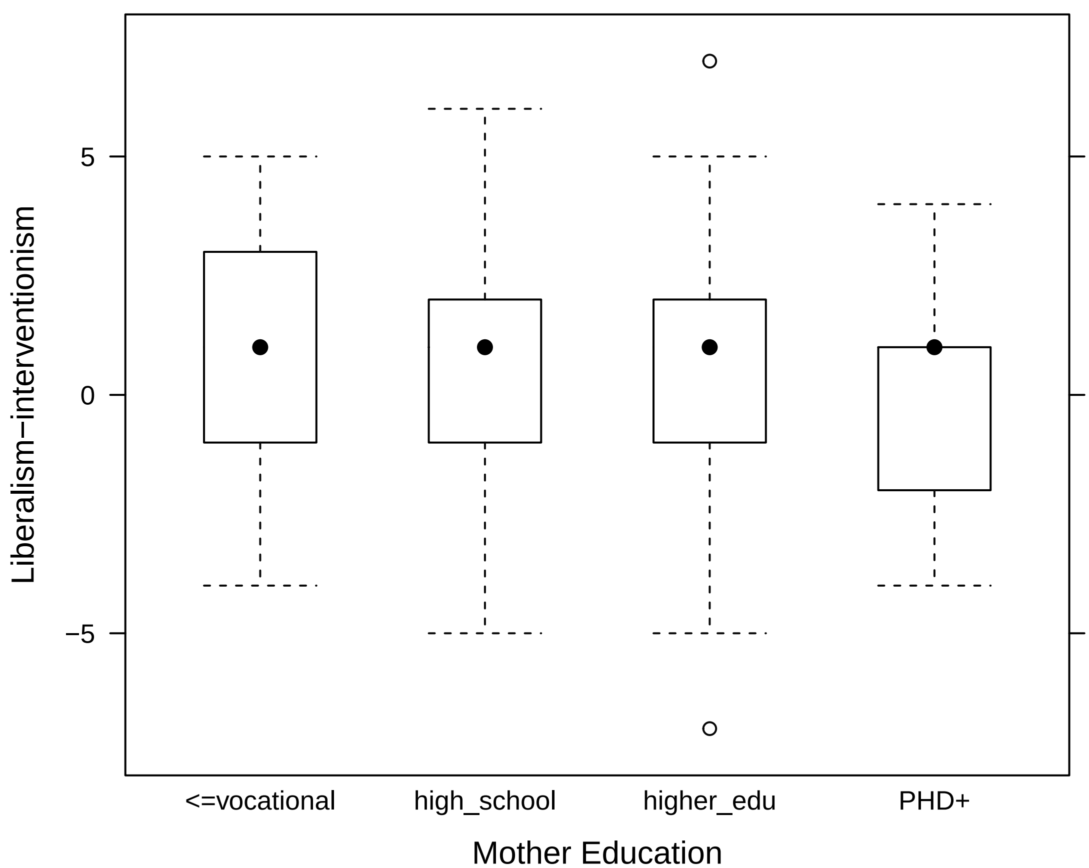
A formal test confirms this supposition. There is no significant relationship between the variables.

```
##
## Call:
```

```
## lm(formula = libsoc ~ father_edu, data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7.3068 -1.5814  0.4054  1.6932  6.6932
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)             0.4628     0.2051   2.256   0.0244 *
## father_eduhigh_school   0.1318     0.2765   0.477   0.6339
## father_eduhigher_edu   -0.1560     0.2497  -0.625   0.5323
## father_eduPHD+          0.1186     0.4006   0.296   0.7673
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.256 on 559 degrees of freedom
##   (62 observations deleted due to missingness)
## Multiple R-squared:  0.003121,   Adjusted R-squared:  -0.002229
## F-statistic: 0.5834 on 3 and 559 DF,  p-value: 0.6261
```

Liberalism-interventionism and mother education

In this case it seems that the higher mother education is the more centrist attitudes a child has.




```
##     mother_edu libsoc.mean libsoc.sd
```

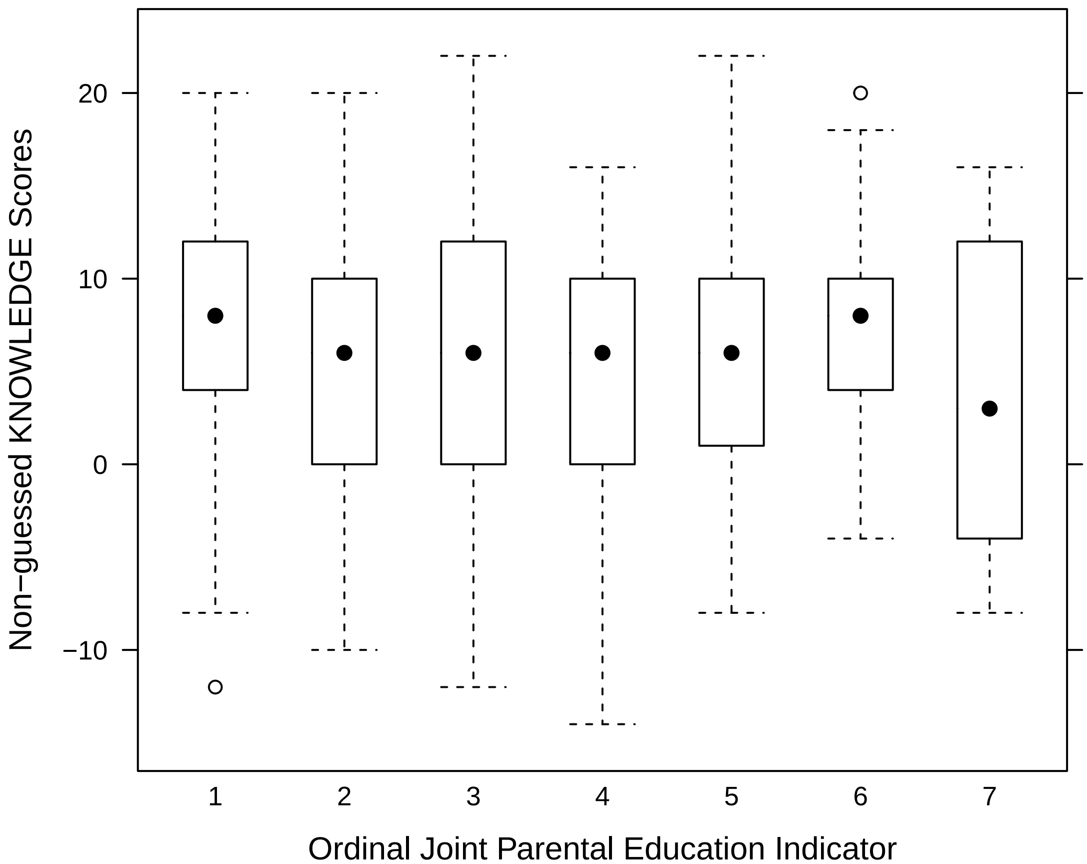
```
## 1 <=vocational   0.7187500  2.333121
## 2  high_school   0.6030151  2.095737
## 3   higher_edu   0.2820513  2.352472
## 4         PHD+   0.0000000  2.154729
```

However, formal testing does not confirm this.

```
##
## Call:
## lm(formula = libsoc ~ mother_edu, data = data)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -7.282 -1.603  0.397  1.718  6.718
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)             0.7187     0.2816   2.552    0.011 *
## mother_eduhigh_school  -0.1157     0.3238  -0.357    0.721
## mother_eduhigher_edu   -0.4367     0.3129  -1.396    0.163
## mother_eduPHD+         -0.7188     0.5043  -1.425    0.155
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.253 on 561 degrees of freedom
##   (60 observations deleted due to missingness)
## Multiple R-squared:  0.007884,   Adjusted R-squared:  0.002579
## F-statistic: 1.486 on 3 and 561 DF,  p-value: 0.2173
```

Knowledge scores and OIJPE

Distributions suggest that there is no clear relationship with the OIJPE scores.




```
##   peduord ngknow.mean knowraw.mean ngknow.sd knowraw.sd
## 1       0    6.857143     18.42857  7.034130   3.517065
## 2       1    5.441176     17.72059  7.029538   3.514769
## 3       2    5.557692     17.77885  7.368032   3.684016
## 4       3    5.190083     17.59504  6.199884   3.099942
## 5       4    5.964912     17.98246  7.020889   3.510444
## 6       5    7.172414     18.58621  6.083167   3.041584
## 7       6    4.142857     17.07143  7.979369   3.989685
```

Formal testing confirms this.

```
##
## Call:
## lm(formula = ngknow ~ peduord, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -19.7227  -5.7186   0.2773   4.2855  16.2814
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  5.734974   0.665892   8.612   <2e-16 ***
## peduord     -0.004095   0.208318  -0.020    0.984
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

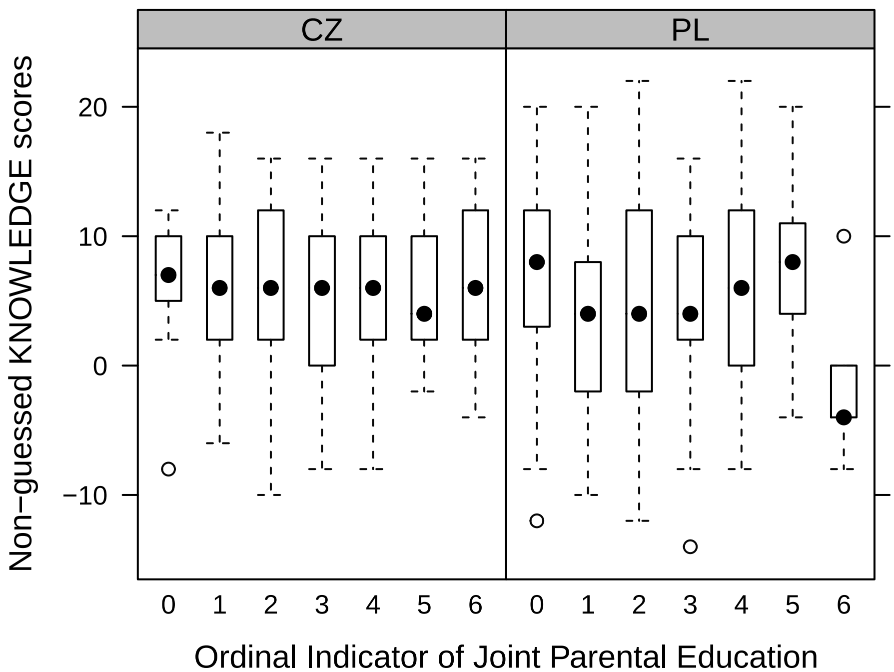
```
##
## Residual standard error: 6.89 on 540 degrees of freedom
##   (83 observations deleted due to missingness)
## Multiple R-squared:  7.156e-07,  Adjusted R-squared:  -0.001851
## F-statistic: 0.0003864 on 1 and 540 DF,  p-value: 0.9843
```

Knowledge scores and OIJPE by country

Additionaly we checked whether the association between the OIJPE scores and the knowledge scores varies between the countries. Distributions conditioned on country show that the knowledge is more or less constant amongst Czech students but rises with parental education amongst Polish students.

```
## $`0.CZ`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -8.000   5.500   7.000   6.167  10.000  12.000       5
##
## $`1.CZ`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -6.000   2.000   6.000   6.419  10.000  18.000       1
##
## $`2.CZ`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -10.00    2.00    6.00    6.04   12.00   16.00       4
##
## $`3.CZ`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -8.000   0.000   6.000   5.297   9.500  16.000       9
##
## $`4.CZ`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -8.000   2.000   6.000   5.108   9.500  16.000       7
##
## $`5.CZ`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -2.000   2.000   4.000   6.154  10.000  16.000
##
## $`6.CZ`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -4.000   2.000   6.000   7.111  12.000  16.000       3
##
## $`0.PL`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -12.000   3.000   8.000   7.217  12.000  20.000
##
## $`1.PL`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -10.00   -2.00    4.00    3.76    8.00   20.00       2
##
## $`2.PL`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
## -12.000  -1.500   4.000   5.111  11.500  22.000       1
##
## $`3.PL`
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
## -14.000   2.000   4.000   5.021  10.000  16.000       3
##
## $`4.PL`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -8.000   0.000   6.000   6.619  12.000  22.000       3
##
## $`5.PL`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    -4.0     4.0     8.0     8.0    10.5    20.0       1
##
## $`6.PL`
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    -8.0    -4.0    -4.0    -1.2     0.0    10.0
```




```
## $CZ
##
##    0    1    2    3    4    5    6 <NA>
##   17   44   54   83   81   13   12    6
##
## $PL
##
##    0    1    2    3    4    5    6 <NA>
##   23   27   55   50  100   17    5   38
```

Since there is a huge sampling error in the highest OIJPE groups (this is vivid in the highest OIJPE group in Poland that has very low mean score and only 5 respondents) due to low frequencies, we conduct formal tests using a subsample limited to OIJPE scores ≤ 5.

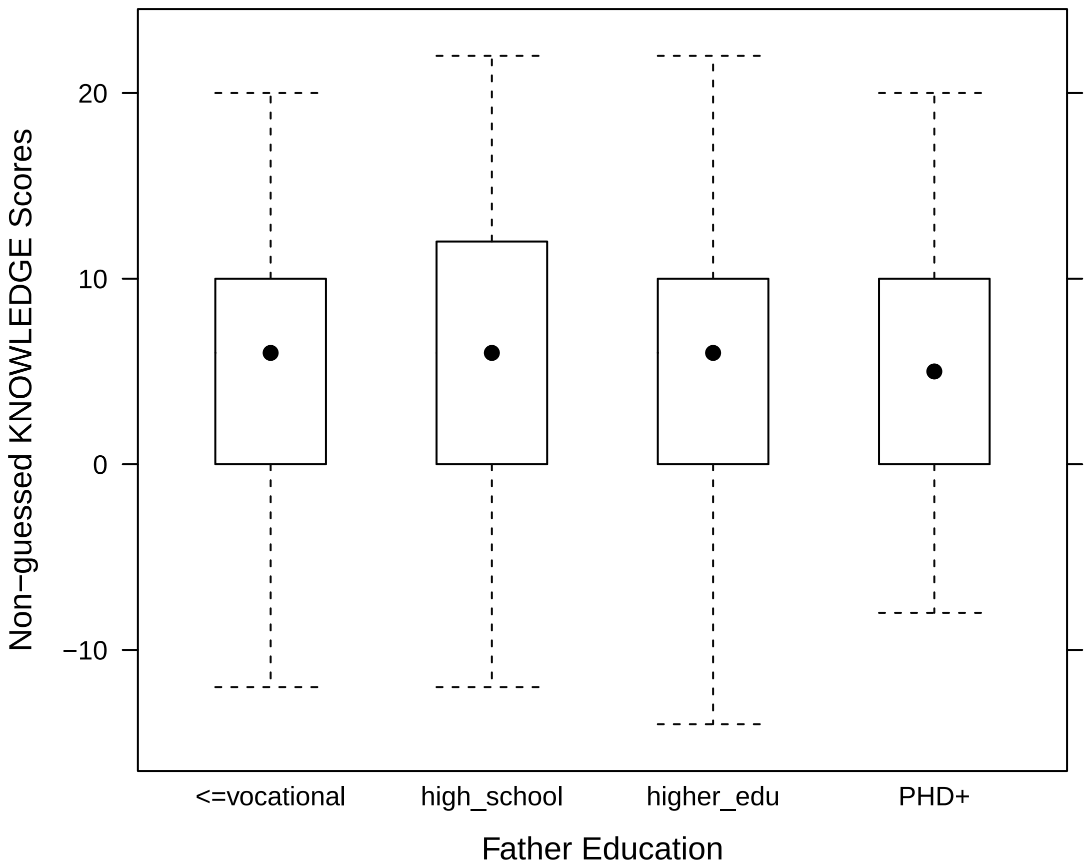
```
##
## Call:
```

```
## lm(formula = ngknow ~ peduord * country, data = data, subset = data$peduord <=
##     5)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -19.9491  -5.2096   0.1338   4.7360  16.4297
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)         6.4685     0.9898   6.535 1.51e-10 ***
## peduord            -0.3011     0.3283  -0.917    0.359
## countryPL          -1.6559     1.3756  -1.204    0.229
## peduord:countryPL   0.6800     0.4463   1.524    0.128
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.859 on 524 degrees of freedom
##   (80 observations deleted due to missingness)
## Multiple R-squared:  0.004884,   Adjusted R-squared:  -0.0008135
## F-statistic: 0.8572 on 3 and 524 DF,  p-value: 0.4632
```

Clearly even in this subsample there is no assocaition in both countries.

Knowledge scores and father education

Again distributions show no pattern.




```
##     father_edu ngknow.mean knowraw.mean ngknow.sd knowraw.sd
## 1 <=vocational    5.155172     17.57759  7.033588   3.516794
## 2  high_school    6.055556     18.02778  6.915856   3.457928
## 3   higher_edu    5.777778     17.88889  6.832107   3.416053
## 4         PHD+    5.750000     17.87500  6.735859   3.367929
```

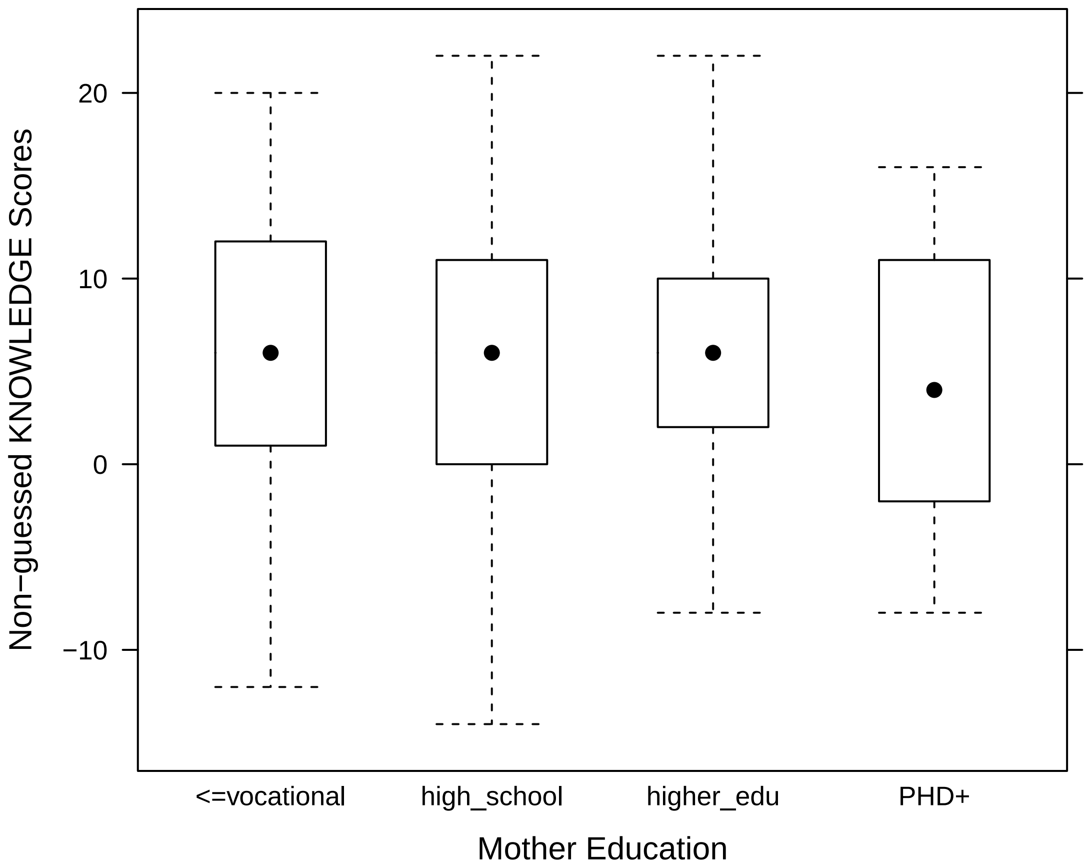
And formal testing confirms it too.

```
##
## Call:
## lm(formula = ngknow ~ father_edu, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -19.7778  -5.4526   0.2222   4.8448  16.2222
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)              5.1552     0.6398   8.057 5.04e-15 ***
## father_eduhigh_school    0.9004     0.8597   1.047    0.295
## father_eduhigher_edu     0.6226     0.7777   0.801    0.424
## father_eduPHD+           0.5948     1.2635   0.471    0.638
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 6.891 on 539 degrees of freedom
##   (82 observations deleted due to missingness)
## Multiple R-squared:  0.002108,   Adjusted R-squared:  -0.003446
## F-statistic: 0.3795 on 3 and 539 DF,  p-value: 0.7678
```

Knowledge scores and mother education

No clear pattern in distributions.




```
##     mother_edu ngknow.mean knowraw.mean ngknow.sd knowraw.sd
## 1 <=vocational    6.237288     18.11864  6.919087   3.459543
## 2  high_school    5.560209     17.78010  7.001901   3.500951
## 3   higher_edu    5.835821     17.91791  6.746556   3.373278
## 4         PHD+    4.518519     17.25926  7.515985   3.757992
```

Formal testing shows that indeed there is no association between the variables.

```
##
## Call:
## lm(formula = libsoc ~ mother_edu, data = data)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -7.282 -1.603  0.397  1.718  6.718
```

```
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)            0.7187     0.2816   2.552    0.011 *
## mother_eduhigh_school  -0.1157     0.3238  -0.357    0.721
## mother_eduhigher_edu   -0.4367     0.3129  -1.396    0.163
## mother_eduPHD+         -0.7188     0.5043  -1.425    0.155
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.253 on 561 degrees of freedom
##   (60 observations deleted due to missingness)
## Multiple R-squared:  0.007884,   Adjusted R-squared:  0.002579
## F-statistic: 1.486 on 3 and 561 DF,  p-value: 0.2173
```

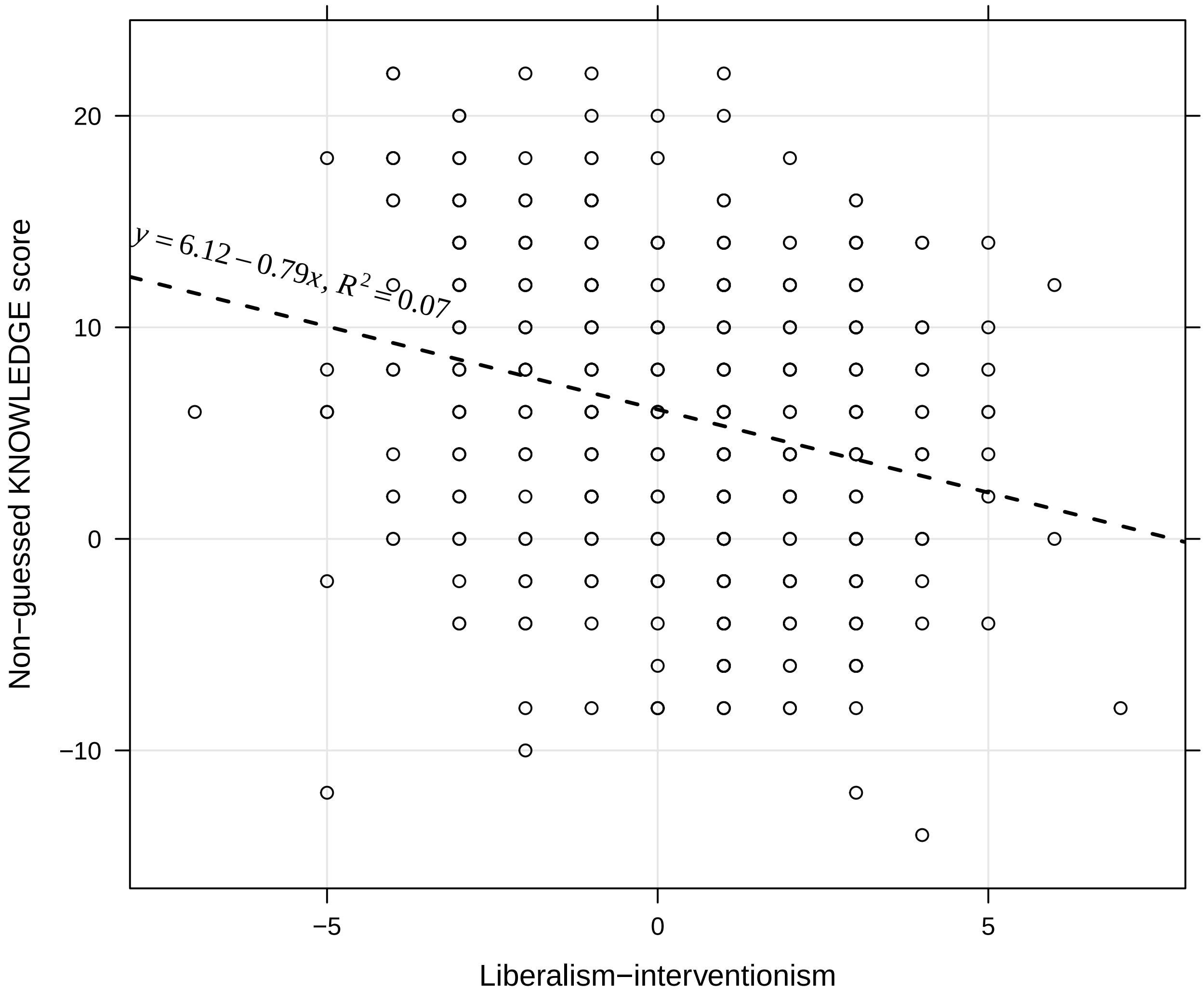
Knowledge scores and the liberalism-interventionism scale

Now we turn to the problem of the relationship between the knowledge scores and the liberalism-interventionism scale scores. Simple correlation coefficient indicates that there may be some sort of an association. The negative value of the coefficient shows that the negative pole of the liberalism-interventionism scale (that is liberalism) is related to better knowledge scores.

```
##        libsc ngknw
## libsoc  1.00
## ngknow -0.26  1.00
```

Regression model shows that indeed there is significant relationship of such kind; liberalism-interventionism scale scores are associated with 6.9% of the variance of the knowledge scores and on average the stronger liberal attitude of a person is, the better knowledge score he or she gets. According to the model equation (see the plot below) a person with a score of -5 on the liberalism-interventionism (quite strong liberal attitude) axis would give about 10 nonrandom correct answers, while a person with a score of 5 (quite strong interventionist attitude) on the axis would give only about 2 nonrandom correct answers.

```
##
## Call:
## lm(formula = ngknow ~ libsoc, data = data, subset = knowIV ==
##     0)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -22.047  -4.904   0.239   5.096  16.668
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   6.1183     0.2845  21.502  < 2e-16 ***
## libsoc       -0.7858     0.1229  -6.396 3.43e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.595 on 547 degrees of freedom
##   (19 observations deleted due to missingness)
## Multiple R-squared:  0.06958,    Adjusted R-squared:  0.06788
## F-statistic: 40.91 on 1 and 547 DF,  p-value: 3.427e-10
```



Knowledge scores and the liberalism-interventionism scale while controlling for country

Now we extends the model in order to control for the effect of a country, since the dynamics of this relationship may differ between Poland and Czech Republic. Correlation coefficients in countries suggest that the effect may be weaker in amongst Czech students.

```
## Polish sample
```

```
##        libsc ngknw
## libsoc  1.00
## ngknow -0.32  1.00
```

```
## Czech sample
```

```
##        libsc ngknw
## libsoc  1.00
## ngknow -0.19  1.00
```

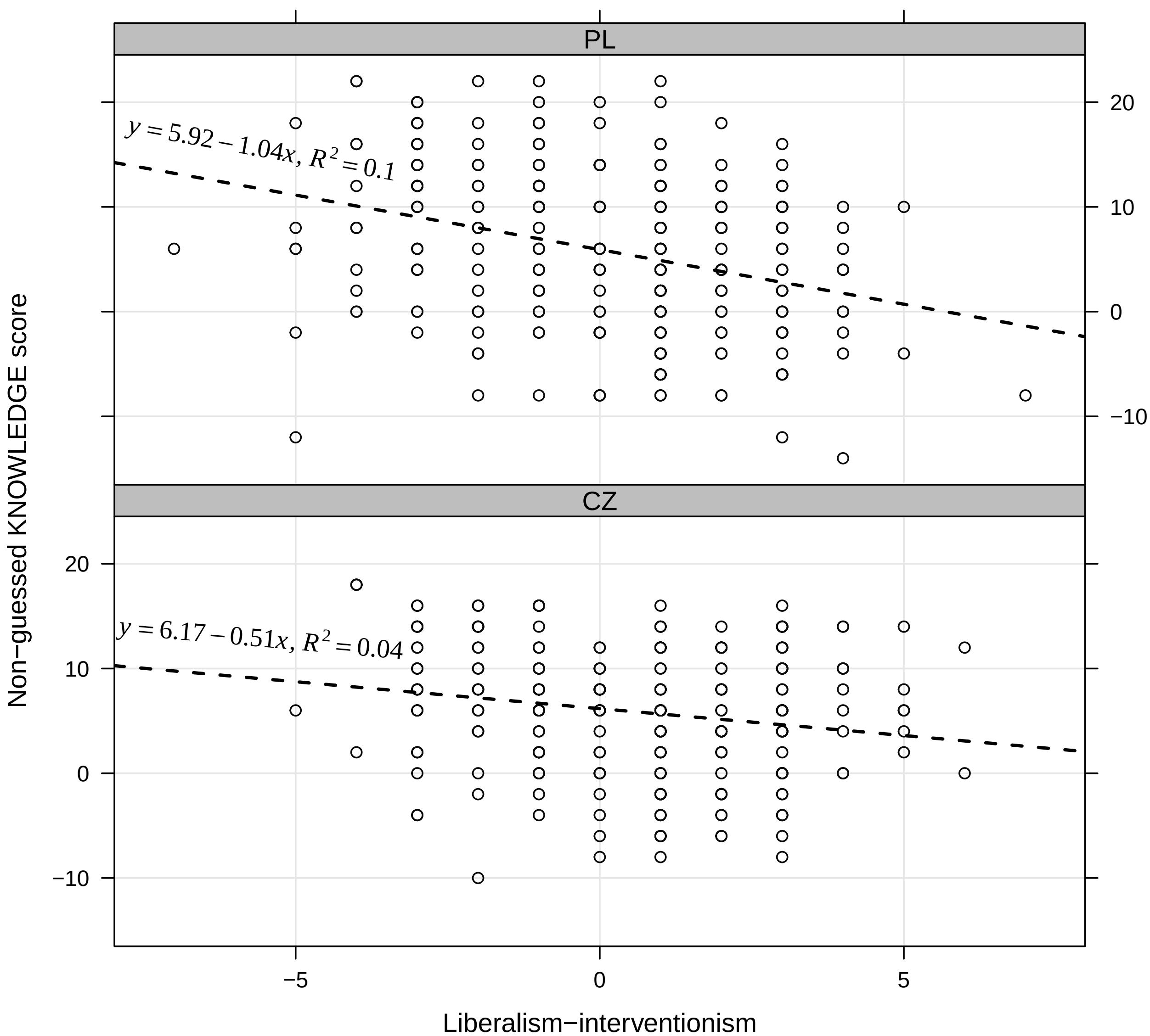
Formal test indeed showed that there is a significant effect of an interaction between country and liberalism-interventionism, which cause the effect in the Polish sample to be more than two times stronger than the corresponding effect in the Czech sample. In the Polish sample 10.5% of the variance of the knowledge scores is associated with the liberalism-interventionism scale scores, while in the Czech sample it is only 3.5%. In the Joint Sample it is 7.8%.

```
##
## Call:
## lm(formula = ngknow ~ libsoc * country, data = data, subset = knowIV ==
##     0)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -23.1270  -4.7945   0.1639   5.0392  17.1223
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)        6.1690     0.4125  14.954  < 2e-16 ***
## libsoc            -0.5137     0.1813  -2.833  0.00479 **
## countryPL         -0.2497     0.5723  -0.436  0.66275
## libsoc:countryPL  -0.5279     0.2474  -2.133  0.03333 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.576 on 545 degrees of freedom
##   (19 observations deleted due to missingness)
## Multiple R-squared:  0.07831,    Adjusted R-squared:  0.07323
## F-statistic: 15.43 on 3 and 545 DF,  p-value: 1.193e-09
```

```
##
## Call:
## lm(formula = ngknow ~ libsoc, data = data, subset = knowIV ==
##     0 & country == "PL")
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -23.1270  -5.0439   0.0808   5.1223  17.1223
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   5.9192     0.4345  13.624  < 2e-16 ***
## libsoc       -1.0416     0.1844  -5.649 4.05e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7.202 on 273 degrees of freedom
##   (13 observations deleted due to missingness)
## Multiple R-squared:  0.1047, Adjusted R-squared:  0.1014
## F-statistic: 31.91 on 1 and 273 DF,  p-value: 4.045e-08
```

```
##
## Call:
## lm(formula = ngknow ~ libsoc, data = data, subset = knowIV ==
```

```
##     0 & country == "CZ")
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -17.1963  -4.1690   0.3447   4.3857  11.3720
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   6.1690     0.3689  16.721  < 2e-16 ***
## libsoc       -0.5137     0.1622  -3.167  0.00171 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.881 on 272 degrees of freedom
##   (6 observations deleted due to missingness)
## Multiple R-squared:  0.03557,    Adjusted R-squared:  0.03203
## F-statistic: 10.03 on 1 and 272 DF,  p-value: 0.001713
```



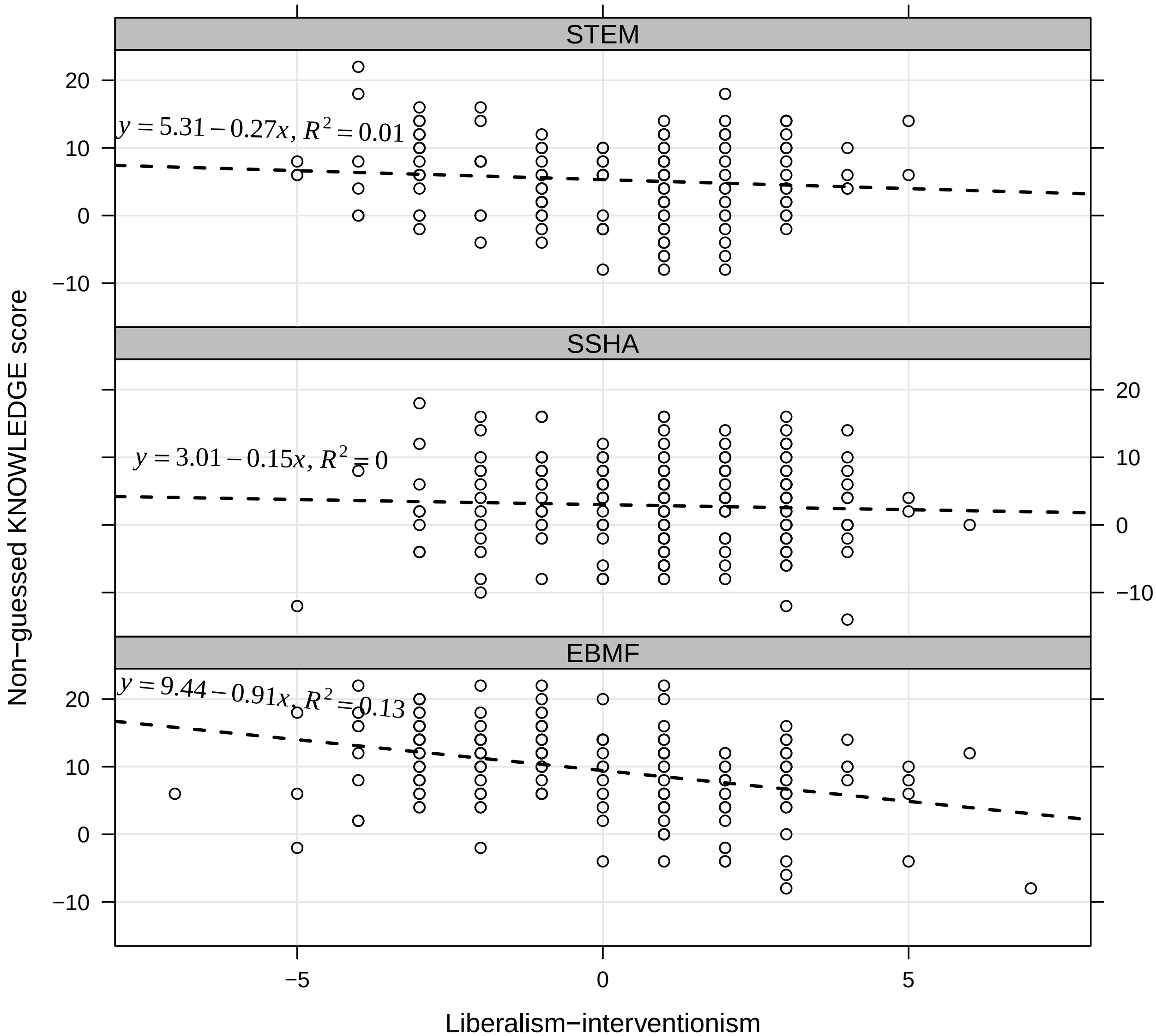
Knowledge scores and the liberalism-interventionism scale while controlling for education type

Correlation coefficients in group suggest that the relationship is much stronger in the EBMF group.

```
## EBMF

##        libsc ngknw
## libsoc  1.00
## ngknow -0.36  1.00

## SSHA

##        libsc ngknw
## libsoc  1.00
## ngknow -0.05  1.00

## STEM

##        libsc ngknw
## libsoc  1.0
## ngknow -0.1   1.0
```

Formal test confirms that there is an interaction between education type and liberalism-interventionism scores. The model parameters show that in this case the interaction means that in the EBMF group association between liberalims-interventionism scoresn and knowledge scores is much stronger (in SSHA group it is even non-existent - see the equations on the plot). The model with interaction explains about 22.7% of the variance (fractions of variance explained in the subgroup are on the plot).

```
##
## Call:
## lm(formula = ngknow ~ libsoc * eduprog3, data = data, subset = knowIV ==
##     0)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16.4036  -4.3507   0.7367   4.3871  15.6243
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)           9.4381     0.4414  21.384  < 2e-16 ***
## libsoc               -0.9126     0.1772  -5.149 3.67e-07 ***
## eduprog3SSHA         -6.4313     0.6454  -9.965  < 2e-16 ***
## eduprog3STEM         -4.1239     0.6634  -6.217 1.02e-09 ***
## libsoc:eduprog3SSHA   0.7618     0.2779   2.741  0.00633 **
## libsoc:eduprog3STEM   0.6472     0.2819   2.296  0.02207 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.017 on 539 degrees of freedom
##   (23 observations deleted due to missingness)
## Multiple R-squared:  0.2266, Adjusted R-squared:  0.2194
## F-statistic: 31.58 on 5 and 539 DF,  p-value: < 2.2e-16
```



Liberalism-interventionism and work experience

Group means clearly show that respondents with no work experience on average have a little bit stronger interventionist attitudes. There is also a difference, although much smaller between up to 1 year of experience and more.

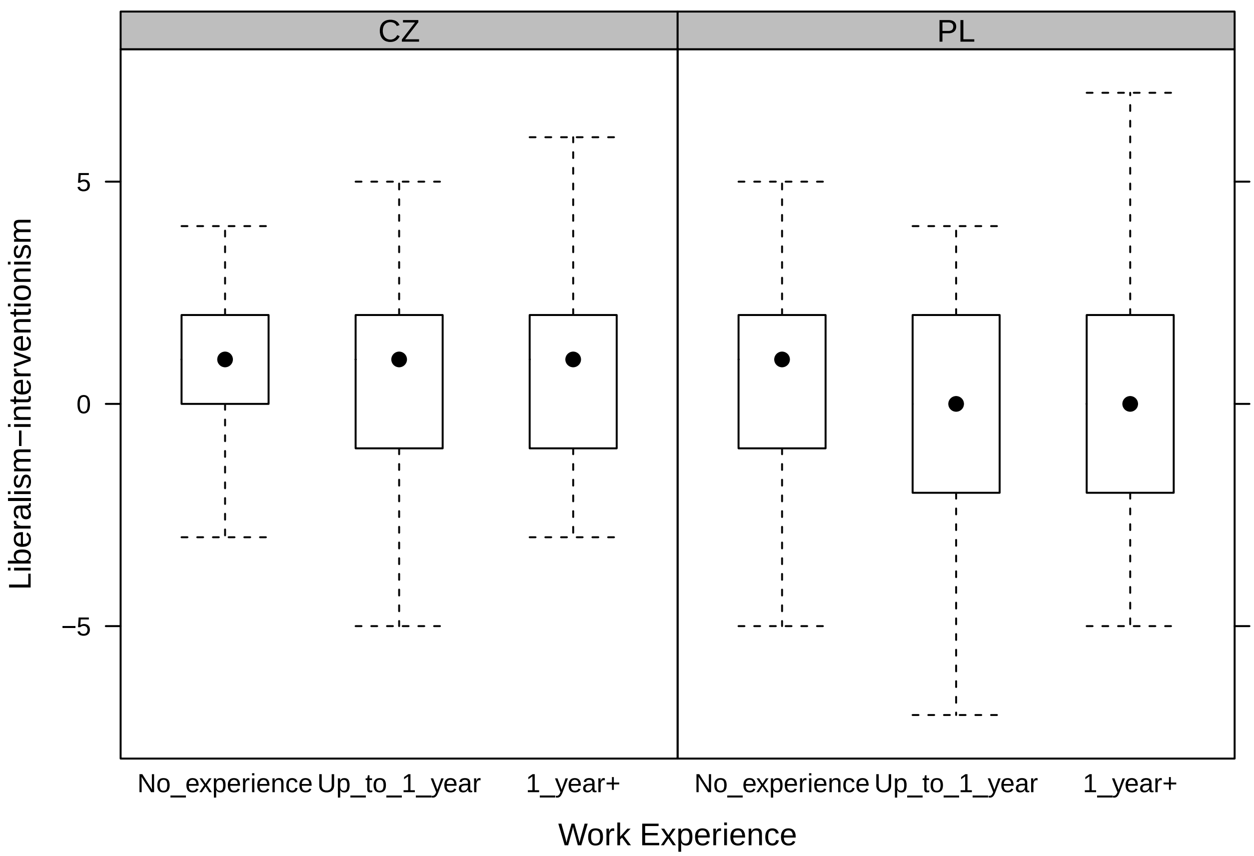

```
##   work_experience libsoc.mean libsoc.sd
## 1   No_experience   0.7905405  2.087388
## 2    Up_to_1_year   0.1300448  2.237305
## 3         1_year+   0.3313609  2.298348
```

We test statistical significance of this observation using an ANOVA model with contrasts. The first contrast test wheter the first group (no experience) has higher mean of liberalism-interventionism than the other two groups on average. The second contrast test whether the two groups of people with experience do differ.

```
##
## Call:
## lm(formula = libsoc ~ wexp, data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7.1300 -1.3314  0.2095  1.6686  6.6686
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.4173     0.0968   4.311 1.93e-05 ***
## wexp1         0.5598     0.2145   2.611  0.00929 **
## wexp2        -0.2013     0.2261  -0.890  0.37365
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.217 on 537 degrees of freedom
##   (85 observations deleted due to missingness)
## Multiple R-squared:  0.01466,    Adjusted R-squared:  0.01099
## F-statistic: 3.994 on 2 and 537 DF,  p-value: 0.01898
```

We see that the first contrast (wexp1 in the output table) is significant and that the second one is not. Therefore we conclude that students who have work experience have slightly weaker interventionist attitudes (the model retains about 1.5% of the variance of the liberalism-interventionism scores).

We also checked whether there are differences in regard to this effect between the countries. We found out that it is not the case - interaction effect is not significant. Although median positions suggest that the effect is more vivid in Poland (see the plot). However, due to the lack of a formal proof of the significance, we will make no further inquiries into it.




```
## Analysis of Variance Table
##
## Response: libsoc
##               Df  Sum Sq Mean Sq F value   Pr(>F)
## wexp           2   39.26  19.629  4.0527 0.017913 *
## country        1   51.74  51.742 10.6828 0.001151 **
## wexp:country   2    1.03   0.517  0.1067 0.898816
## Residuals    534 2586.40   4.843
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Knowledge scores and work experience

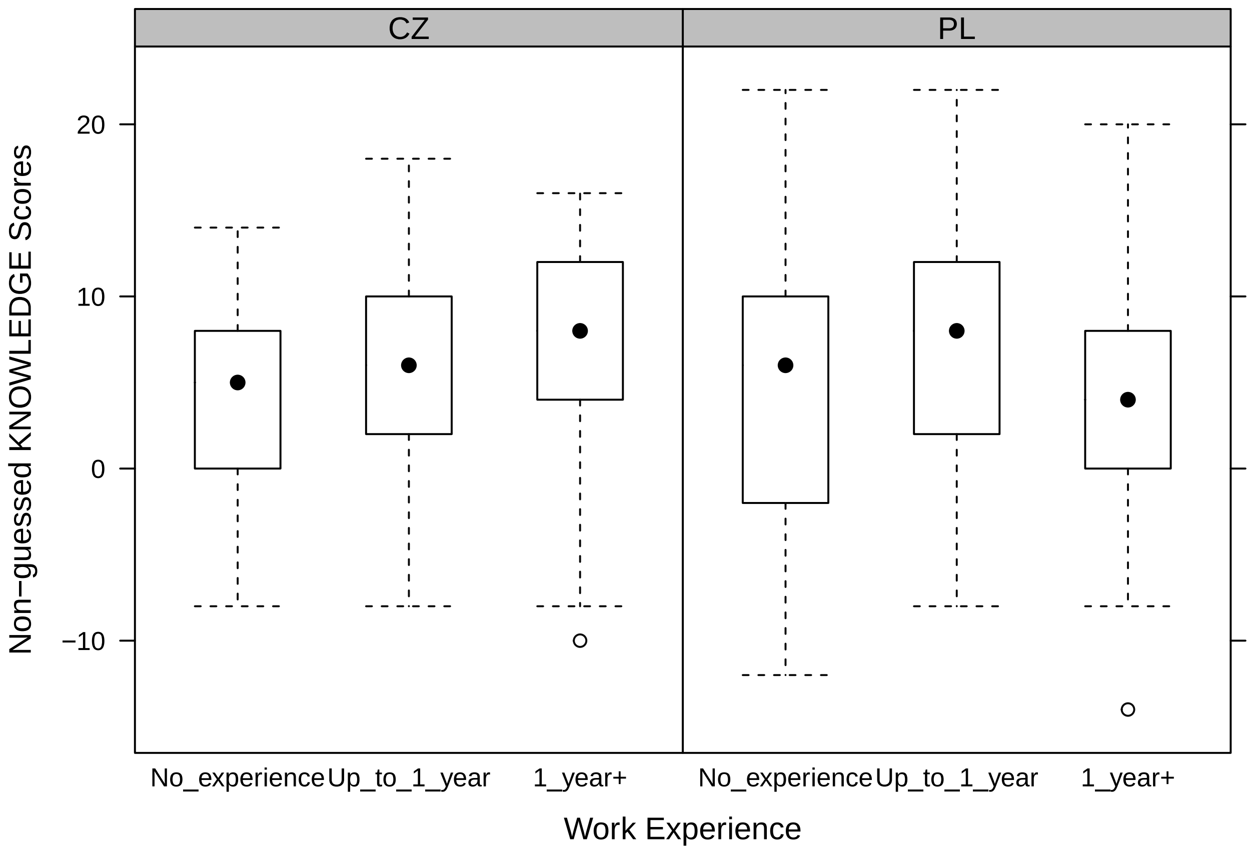
Again we see that people with no work experience tend to have lower scores on average than those with some experience. The difference between the other two groups is much smaller and probably not significant.


```
##            wexp ngknow.mean knowraw.mean ngknow.sd knowraw.sd
## 1 No_experience    4.842857     17.42143  6.517571   3.258785
## 2  Up_to_1_year    6.741784     18.37089  6.919619   3.459809
## 3       1_year+    6.024845     18.01242  6.833694   3.416847
```

We test significance of this observation with a linera model with contrasts analogous to the ones from the previous section. And yet again we see that the first one is significant (so students with no work experience tend to have lower knowledge scores), while the second one is not (there is no difference between those with up to 1 year of experience and those with more). The model retains about 1.3% of the variance of the knowledge scores.

```
##
## Call:
## lm(formula = ngknow ~ wexp, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -20.0248  -4.7418  -0.0248   5.2582  17.1571
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   5.8698     0.3039  19.317   <2e-16 ***
## wexp1        -1.5405     0.6741  -2.285   0.0227 *
## wexp2         0.7169     0.7086   1.012   0.3121
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.785 on 511 degrees of freedom
##   (111 observations deleted due to missingness)
## Multiple R-squared:  0.01279,    Adjusted R-squared:  0.008924
## F-statistic:  3.31 on 2 and 511 DF,  p-value: 0.03732
```

Additionaly we tested the difference between the countries. We found that the interaction effect is nearly significant (plots in groups also suggest interaction by which knowledge of Czech students grows with the experience, while knowledge of Polish students grow with the first year of experience and then suddenly diminishes; however we have to leave the question of whether this is a true effect or just noise unanswered due to the lack of formal significance).




```
## Analysis of Variance Table
##
## Response: ngknow
##               Df  Sum Sq Mean Sq F value  Pr(>F)
## wexp           2   304.8 152.379  3.3293 0.03660 *
## country        1     3.2   3.235  0.0707 0.79044
## wexp:country   2   273.4 136.703  2.9868 0.05133 .
## Residuals    508 23250.6  45.769
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

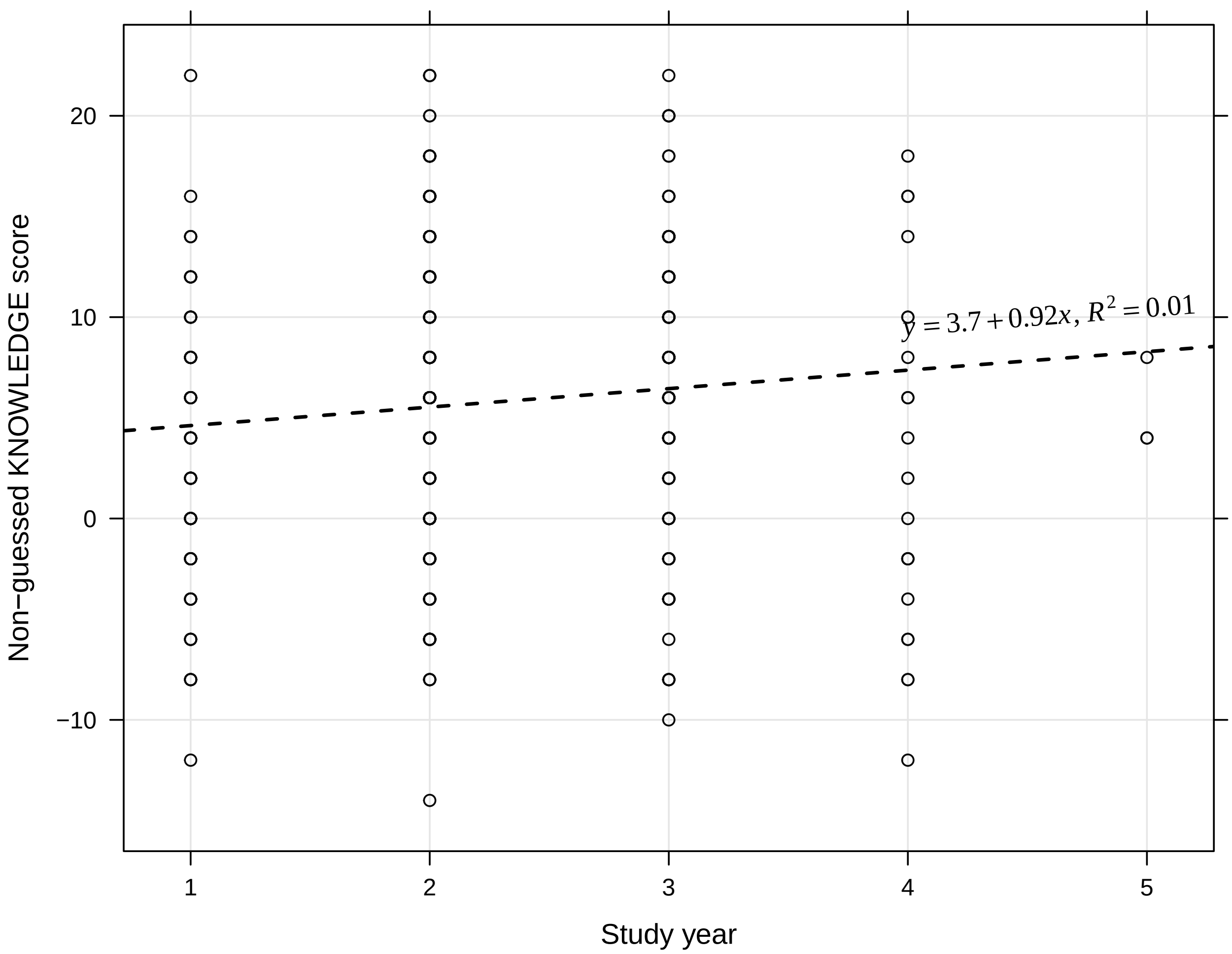
Knowledge and liberlism-interventionism scores and study year

Now we look at the influence of time spent at university on the knowledge scores and the liberalism-interventionism dimension. Correlation tests prove that there is significant association only in the case of the knowledge scores. Therefore we will analyze further only this variable.

```
## Call:corr.test(x = data[, c("libsoc", "ngknow", "uniyear")])
```

```
## Correlation matrix
##         libsoc ngknow uniyear
## libsoc    1.00  -0.26     0.0
## ngknow   -0.26   1.00     0.1
## uniyear   0.00   0.10     1.0
## Sample Size
##         libsoc ngknow uniyear
## libsoc     603    549     592
## ngknow     549    568     558
## uniyear    592    558     612
## Probability values (Entries above the diagonal are adjusted for multiple tests.)
##         libsoc ngknow uniyear
## libsoc    0.00   0.00    0.95
## ngknow    0.00   0.00    0.03
## uniyear   0.95   0.02    0.00
##
##  To see confidence intervals of the correlations, print with the short=FALSE option
```

However, we found that at level of the entire sample only about 1% of the variance of the knowledge scores is explained by study year.




```
##
```

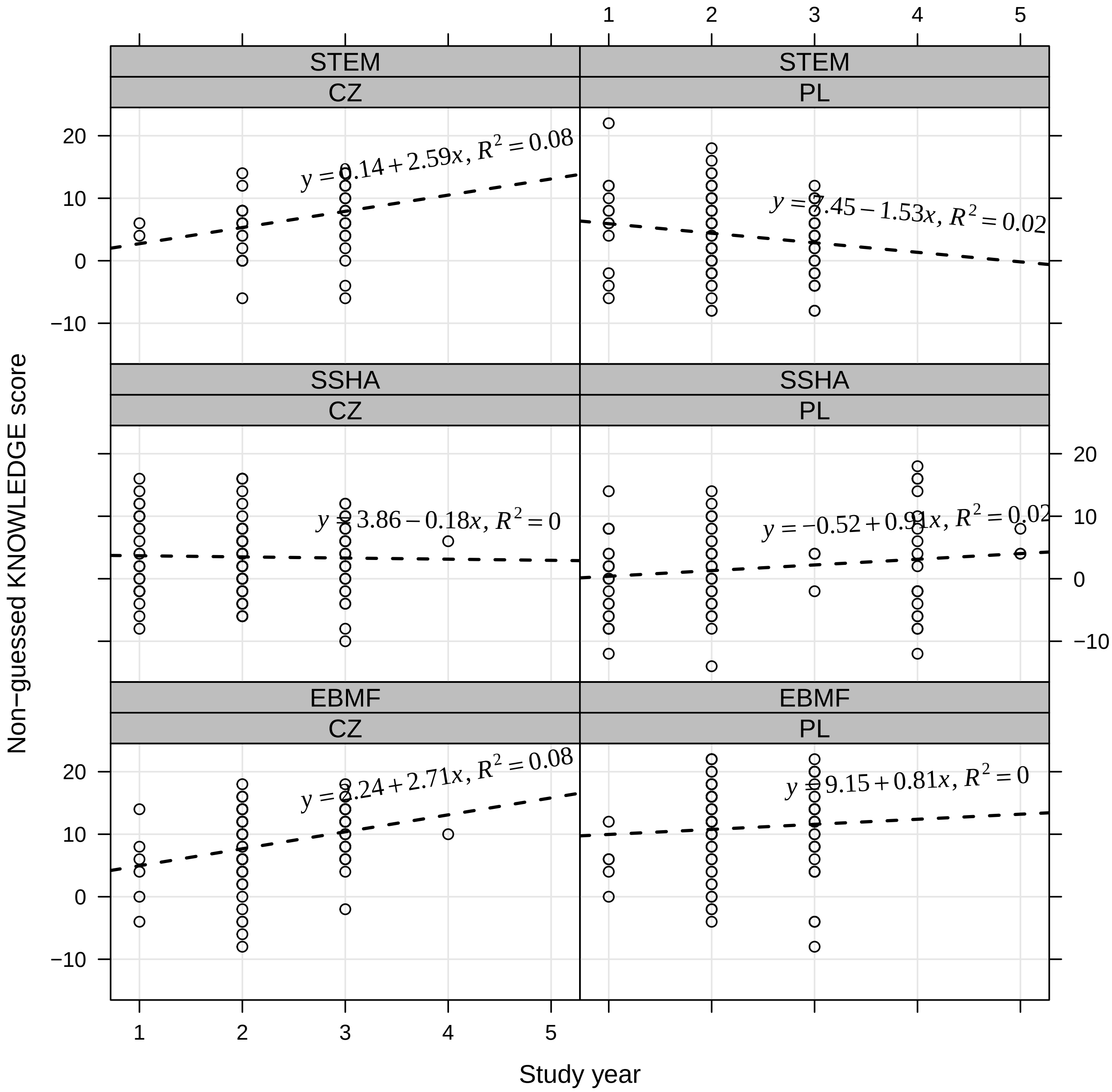
```
## Call:
## lm(formula = ngknow ~ uniyear, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -19.5321  -4.6146   0.4679   5.3854  17.3854
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   3.6972     0.9075   4.074  5.3e-05 ***
## uniyear       0.9174     0.3849   2.384   0.0175 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.785 on 556 degrees of freedom
##   (67 observations deleted due to missingness)
## Multiple R-squared:  0.01011,    Adjusted R-squared:  0.008335
## F-statistic: 5.681 on 1 and 556 DF,  p-value: 0.01748
```

We also conditioned this effect on type of education, since it may be an important factor in this case. However, we found that there is no significant interaction effect - at level of the entire sample there is no significant differences in this regard.

```
## Analysis of Variance Table
##
## Response: ngknow
##                   Df  Sum Sq Mean Sq F value  Pr(>F)
## uniyear            1   266.6  266.60  7.1734 0.00762 **
## eduprog3           2  4947.9 2473.97 66.5658 < 2e-16 ***
## uniyear:eduprog3   2   111.8   55.88  1.5035 0.22327
## Residuals        550 20441.2   37.17
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

This lack of effect may stem from other differences, that is differences between countries. Thus we tested also three-way interaction with country. We found that there is indeed a significant three-way interaction effect.

```
## Analysis of Variance Table
##
## Response: ngknow
##                           Df  Sum Sq Mean Sq F value    Pr(>F)
## uniyear                    1   266.6  266.60  7.4763  0.006456 **
## eduprog3                   2  4947.9 2473.97 69.3761 < 2.2e-16 ***
## country                    1    26.3   26.30  0.7376  0.390821
## uniyear:eduprog3           2   114.8   57.42  1.6103  0.200788
## uniyear:country            1    15.2   15.18  0.4257  0.514396
## eduprog3:country           2   716.0  357.99 10.0390 5.232e-05 ***
## uniyear:eduprog3:country   2   281.4  140.71  3.9458  0.019892 *
## Residuals                544 19399.2   35.66
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



Inspection of the plots show that there is something very interesting going on here. It seems that only Czech students gain more knowledge (mostly EBMF and STEM students) with subsequent years of studies, while Polish students do not (STEM students get even worse).

Formal test of models in the subgroups showed that there are only two groups that have positive association between knowledge scores and study year and these are EBMF and STEM students in Czech Republic.

```
## ######
## GROUP : EBMF in CZ
## ######
##
## Call:
## lm(formula = ngknow ~ uniyear, data = data, subset = data$eduprog3 ==
##     edu & data$country == cntry)
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -15.6715  -3.6715   0.3285   3.6150  10.3285
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.2444     2.2267   1.008   0.3162
## uniyear       2.7135     0.9453   2.870   0.0051 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.408 on 91 degrees of freedom
##   (4 observations deleted due to missingness)
## Multiple R-squared:  0.08303,    Adjusted R-squared:  0.07295
## F-statistic: 8.239 on 1 and 91 DF,  p-value: 0.005097
##
## ######
## GROUP : EBMF in PL
## ######
##
## Call:
## lm(formula = ngknow ~ uniyear, data = data, subset = data$eduprog3 ==
##     edu & data$country == cntry)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -19.583  -3.583   1.227   4.822  11.227
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   9.1530     2.7672   3.308  0.00132 **
## uniyear       0.8099     1.1729   0.691  0.49152
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.478 on 97 degrees of freedom
##   (10 observations deleted due to missingness)
## Multiple R-squared:  0.004892,   Adjusted R-squared:  -0.005367
## F-statistic: 0.4768 on 1 and 97 DF,  p-value: 0.4915
##
## ######
## GROUP : SSHA in CZ
## ######
##
## Call:
## lm(formula = ngknow ~ uniyear, data = data, subset = data$eduprog3 ==
##     edu & data$country == cntry)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -13.3105  -3.4932   0.5068   4.5068  12.5068
##
## Coefficients:
```

```
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   3.8584     1.5460   2.496   0.0138 *
## uniyear      -0.1826     0.7180  -0.254   0.7996
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.549 on 130 degrees of freedom
##   (20 observations deleted due to missingness)
## Multiple R-squared:  0.0004975,  Adjusted R-squared:  -0.007191
## F-statistic: 0.06471 on 1 and 130 DF,  p-value: 0.7996
##
## ######
## GROUP : SSHA in PL
## ######
##
## Call:
## lm(formula = ngknow ~ uniyear, data = data, subset = data$eduprog3 ==
##     edu & data$country == cntry)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -15.300  -5.116  -0.024   3.976  14.884
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -0.5160     1.6701  -0.309    0.758
## uniyear       0.9080     0.6415   1.415    0.161
##
## Residual standard error: 6.947 on 79 degrees of freedom
##   (10 observations deleted due to missingness)
## Multiple R-squared:  0.02473,    Adjusted R-squared:  0.01239
## F-statistic: 2.003 on 1 and 79 DF,  p-value: 0.1609
##
## ######
## GROUP : STEM in CZ
## ######
##
## Call:
## lm(formula = ngknow ~ uniyear, data = data, subset = data$eduprog3 ==
##     edu & data$country == cntry)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -13.9093  -3.3199   0.6801   4.0907   8.6801
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.1411     3.3004   0.043   0.9661
## uniyear       2.5894     1.2717   2.036   0.0474 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.119 on 47 degrees of freedom
##   (12 observations deleted due to missingness)
```

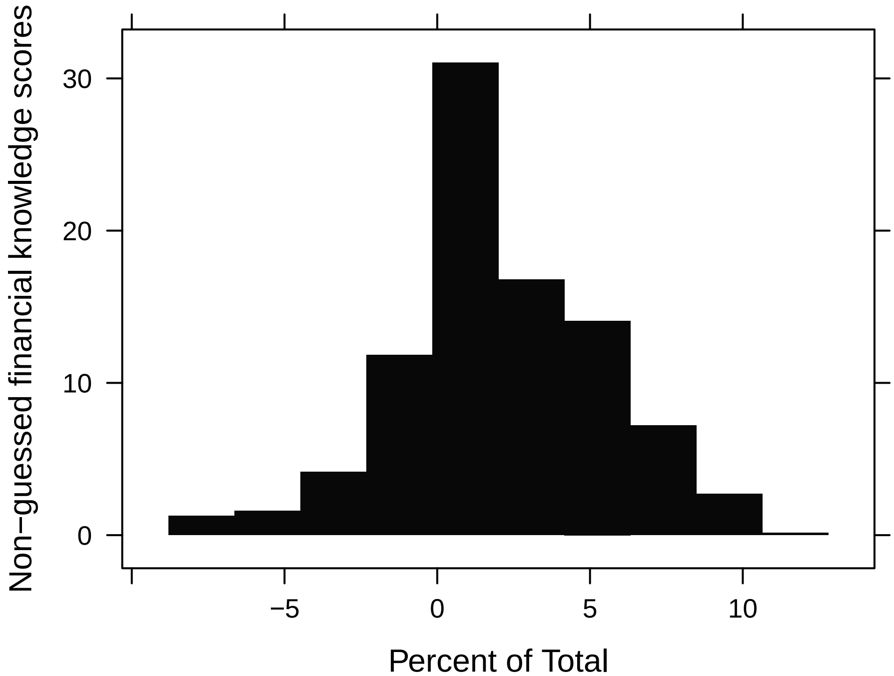
```
## Multiple R-squared:  0.08106,    Adjusted R-squared:  0.06151
## F-statistic: 4.146 on 1 and 47 DF,  p-value: 0.0474
##
## ######
## GROUP : STEM in PL
## ######
##
## Call:
## lm(formula = ngknow ~ uniyear, data = data, subset = data$eduprog3 ==
##     edu & data$country == cntry)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -12.402  -4.402   0.598   4.861  16.072
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   7.4549     2.1767   3.425 0.000893 ***
## uniyear      -1.5265     0.9576  -1.594 0.114086
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.016 on 100 degrees of freedom
##   (29 observations deleted due to missingness)
## Multiple R-squared:  0.02478,    Adjusted R-squared:  0.01503
## F-statistic: 2.541 on 1 and 100 DF,  p-value: 0.1141
```

Financial knowledge scores analysis

For the last part of the analysis we introduce another measure: financial knowledge scores. It is the same as the non-guessed knowledge scores but computed only for the subset of the knowledge items with strictly financial content (this was established by means of expert analysis of the items' content). This subset consists of the following items:

- There are 12 financial items: **k1**, **k2**, **k6**, **k8**, **k12**, **k13**, **k14**, **k18**, **k22**, **k25**, **k28**, **k30**

We see that the distirbution of the scores is nicely symemtric and on average respondents gave a bit more than one nonrandom correct answer.




```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -8.000   0.000   2.000   2.324   6.000  12.000      57
```

Financial knowledge scale scores by country and education type

By country

There is no significant difference in regard to group means between Poland and Czech Republic and the distributions are also very similar.

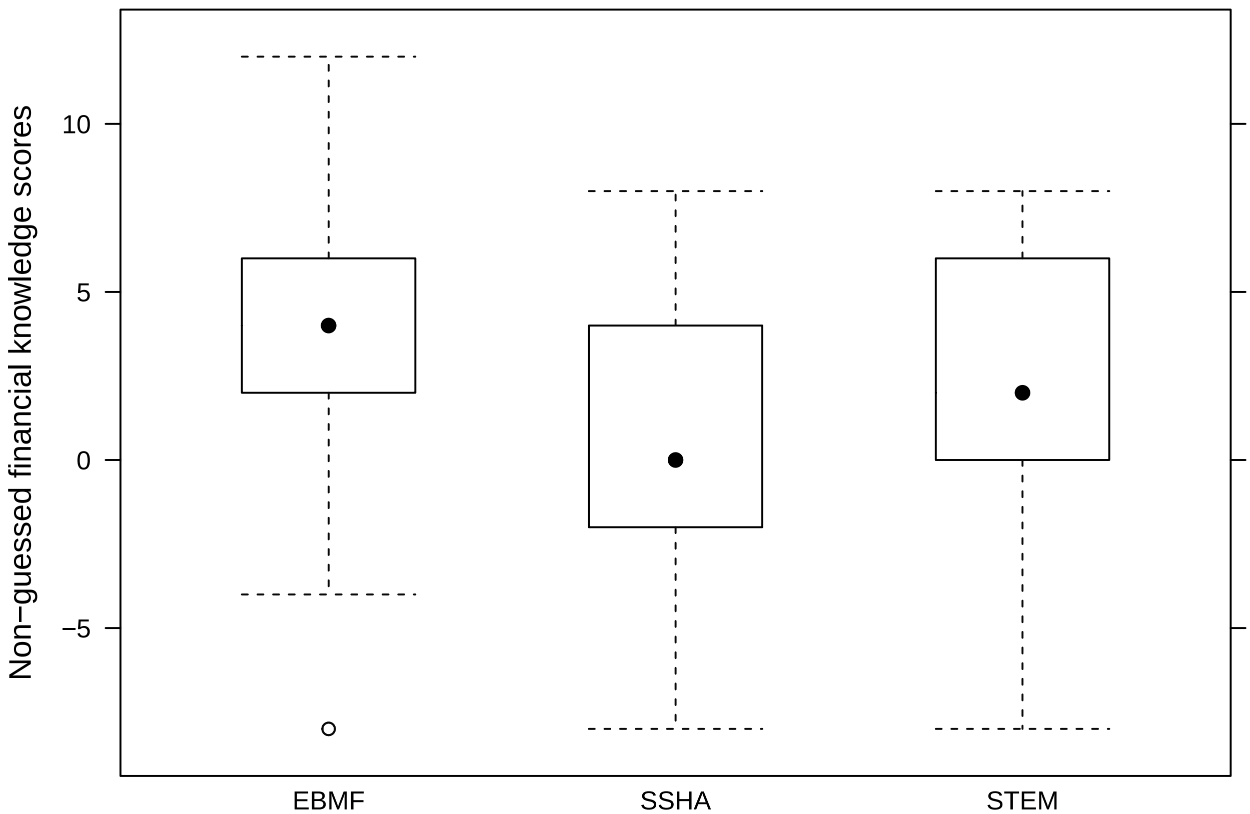
```
## $CZ
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -8.000   0.000   2.000   2.136   4.000  10.000      30
##
## $PL
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -8.000   0.000   2.000   2.507   6.000  12.000      27
```

```
##
##  Welch Two Sample t-test
##
## data:  ngfinance by country
## t = -1.1474, df = 529.07, p-value = 0.2517
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -1.0068069  0.2643466
## sample estimates:
## mean in group CZ mean in group PL
##         2.135714         2.506944
```

By education type

Tests show that both SSHA and STEM students have lower means than EBMF students.

```
## $EBMF
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -8.000   2.000   4.000   4.292   6.000  12.000       6
##
## $SSHA
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
## -8.0000 -2.0000  0.0000  0.6359  4.0000  8.0000      18
##
## $STEM
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##  -8.000   0.000   2.000   2.314   6.000   8.000      31
```

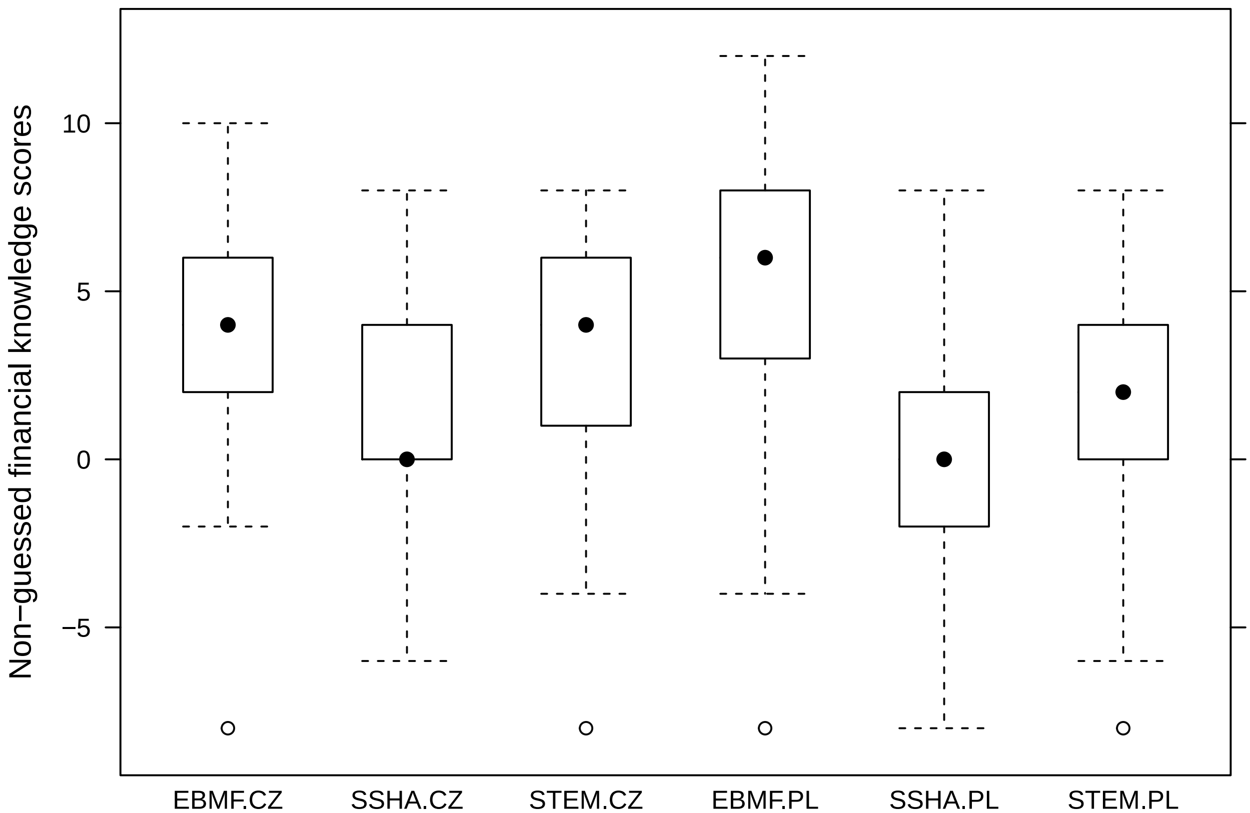



```
##
## Call:
## lm(formula = ngfinance ~ eduprog3, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.2917  -2.3137  -0.2917   3.3641   7.7083
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)    4.2917     0.2565  16.732  < 2e-16 ***
## eduprog3SSHA  -3.6557     0.3521 -10.382  < 2e-16 ***
## eduprog3STEM  -1.9779     0.3852  -5.135 3.89e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.554 on 559 degrees of freedom
##   (63 observations deleted due to missingness)
## Multiple R-squared:  0.1617, Adjusted R-squared:  0.1587
## F-statistic:  53.9 on 2 and 559 DF,  p-value: < 2.2e-16
```

By country and education type

The distributions in the subgroups are clearly different and there is also significant interaction effect of country and education type.




```
## Analysis of Variance Table
##
## Response: ngfinance
##                    Df Sum Sq Mean Sq F value    Pr(>F)
## country             1   23.7   23.66   1.952    0.1629
## eduprog3            2 1338.1  669.07  55.195 < 2.2e-16 ***
## country:eduprog3    2  320.9  160.45  13.236 2.422e-06 ***
## Residuals         556 6739.7   12.12
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Model coefficients show that Polish EBMF students have the mean score (significantly better than Czech EBMF students) and at the same time that Polish SSHA and STEM students have lower mean scores than corresponding Czech students (it is easu to see that on the plot above).

```
##
## Call:
## lm(formula = ngfinance ~ country * eduprog3, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -13.3131  -1.9608   0.6869   2.7957   8.0988
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)               3.2043     0.3610   8.875  < 2e-16 ***
## countryPL                 2.1088     0.5028   4.194 3.18e-05 ***
## eduprog3SSHA             -2.1308     0.4685  -4.548 6.64e-06 ***
## eduprog3STEM             -0.1847     0.6066  -0.304    0.761
## countryPL:eduprog3SSHA  -3.2811     0.7011  -4.680 3.61e-06 ***
## countryPL:eduprog3STEM  -3.1677     0.7806  -4.058 5.66e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.482 on 556 degrees of freedom
##   (63 observations deleted due to missingness)
## Multiple R-squared:  0.1998, Adjusted R-squared:  0.1926
## F-statistic: 27.76 on 5 and 556 DF,  p-value: < 2.2e-16
```

Financial knowledge scores and liberalism-interventionism

There is general slight negative association between liberalism-interventionism scale scores and financial knowledge scale scores (so the stronger interventionist attitudes are, the lower financial scores are).

```
## Analysis of Variance Table
##
## Response: ngfinance
##                  Df Sum Sq Mean Sq F value    Pr(>F)
## libsoc            1  419.0  418.97 33.8037 1.045e-08 ***
## eduprog3          2  997.6  498.81 40.2455 < 2.2e-16 ***
## libsoc:eduprog3   2   45.1   22.54  1.8184    0.1633
## Residuals       539 6680.5   12.39
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Financial knowledge scores and liberalism-interventionism controling for education type and country

However, additional analyses proved that this effect is universal and does not interact with education type and country. In other words it stays more or less the same regardles of these two factors.

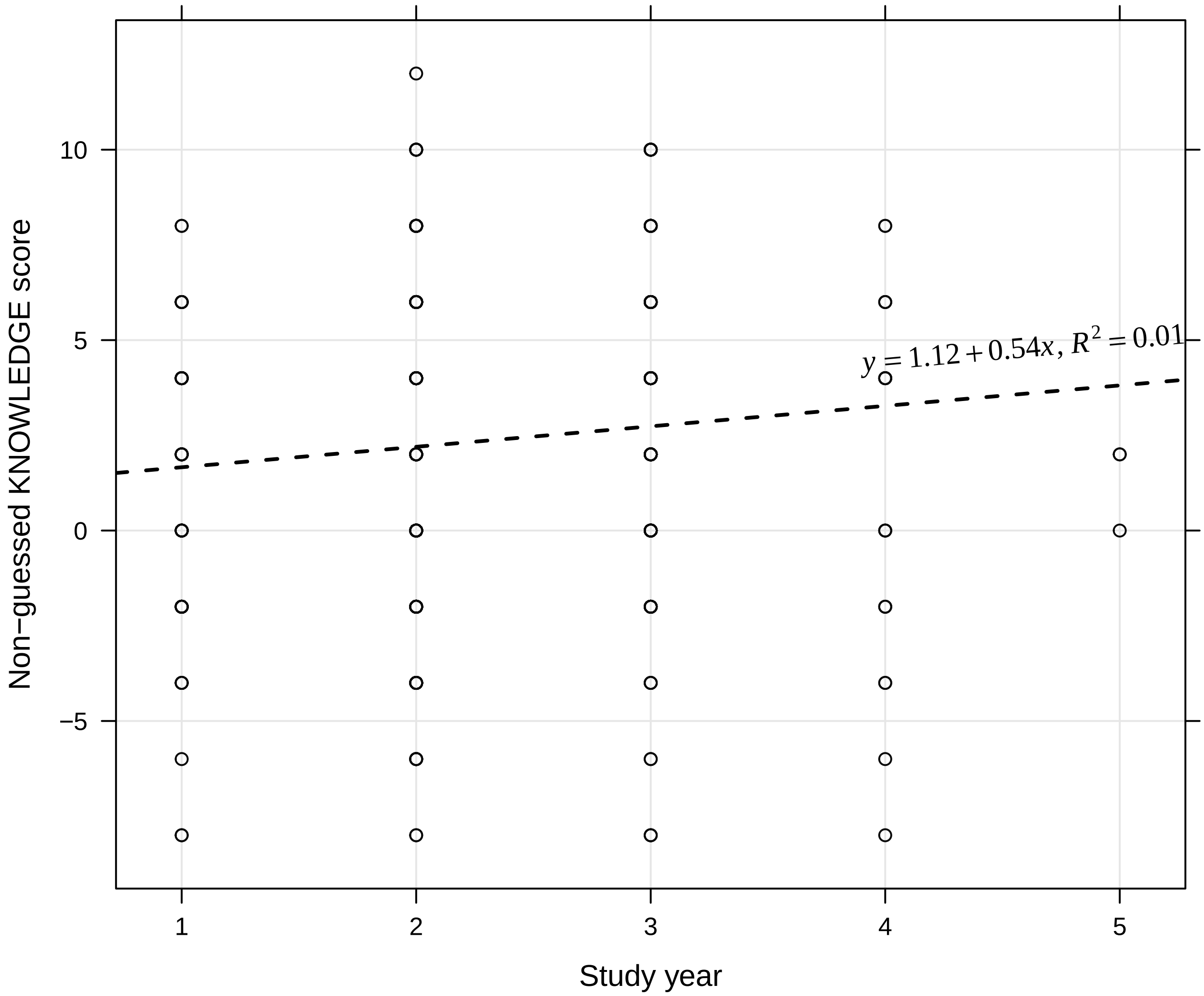
```
## Analysis of Variance Table
##
```

```
## Response: ngfinance
##                 Df Sum Sq Mean Sq F value    Pr(>F)    
## libsoc           1  424.7  424.67 29.9673 6.713e-08 ***
## country          1    5.1    5.05  0.3565    0.5507    
## libsoc:country   1   29.7   29.70  2.0957    0.1483    
## Residuals      545 7723.3   14.17                      
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
## Analysis of Variance Table
## 
## Response: ngfinance
##                         Df Sum Sq Mean Sq F value    Pr(>F)    
## libsoc                   1  419.0  418.97 34.9885 5.933e-09 ***
## country                  1    5.2    5.17  0.4319    0.5114    
## eduprog3                 2  992.7  496.36 41.4511 < 2.2e-16 ***
## libsoc:country           1   29.7   29.70  2.4806    0.1159    
## libsoc:eduprog3          2   43.0   21.52  1.7971    0.1668    
## country:eduprog3         2  262.4  131.20 10.9568 2.171e-05 ***
## libsoc:country:eduprog3  2    7.7    3.87  0.3232    0.7240    
## Residuals              533 6382.4   11.97                      
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Financial knowledge scores and study year

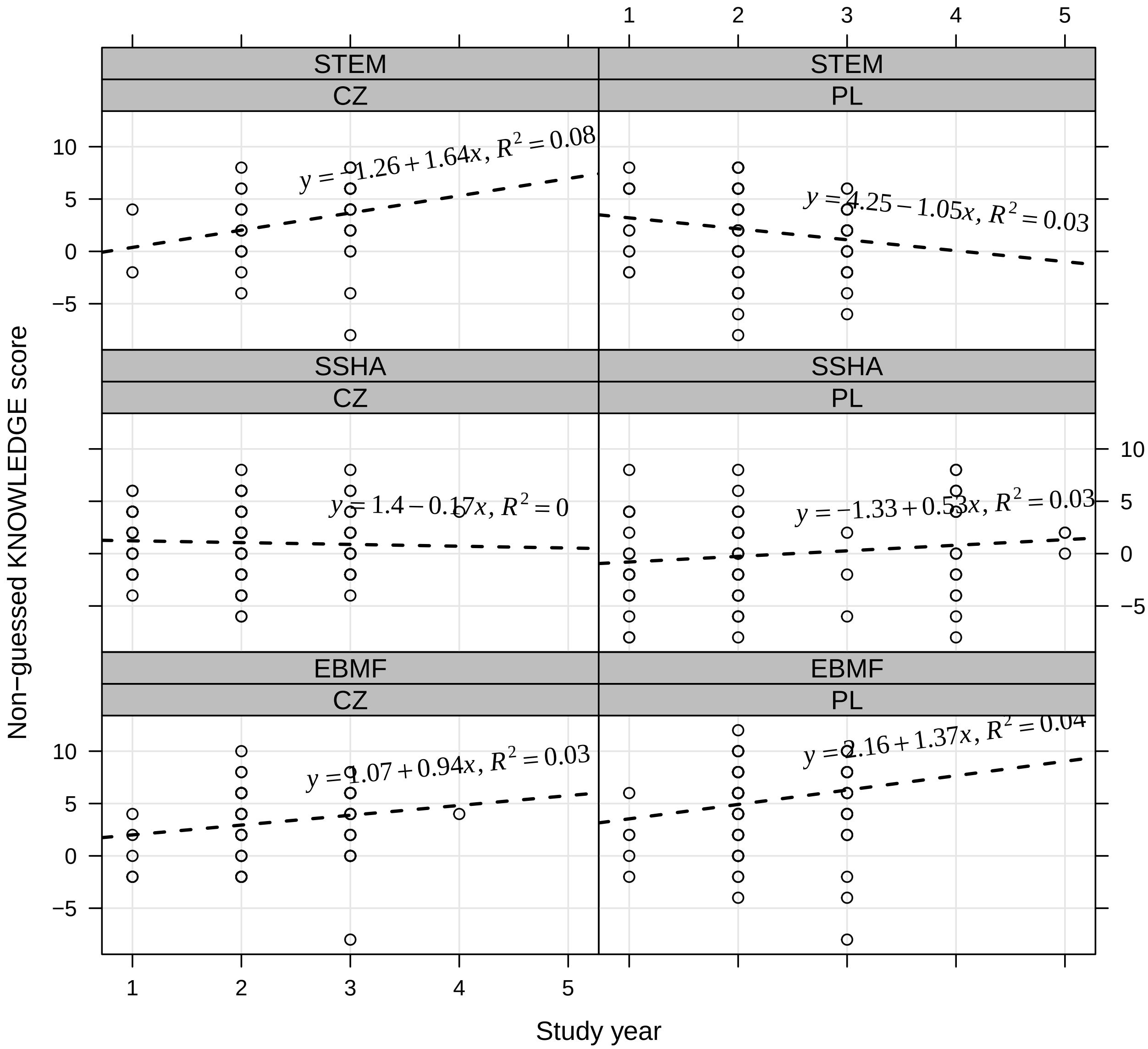
There is also a (slight) general association between financial knowledge scores and study year.




```
##
## Call:
## lm(formula = ngfinance ~ uniyear, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.2735  -2.7363  -0.1991   3.2637   9.8009
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.1247     0.5168   2.176   0.0300 *
## uniyear       0.5372     0.2192   2.451   0.0146 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.864 on 556 degrees of freedom
##   (67 observations deleted due to missingness)
## Multiple R-squared:  0.01069,    Adjusted R-squared:  0.008907
## F-statistic: 6.006 on 1 and 556 DF,  p-value: 0.01457
```

Financial knowledge scores and study year controling for education type and country

There is significant 3-way interaction between study year, contry and education type (see the plot below that depicts it very well). It implies that the association between financiel knowledge scores and study year varies between student groups in Poland and Czech Republic.




```
## Analysis of Variance Table
##
## Response: ngfinance
##                          Df Sum Sq Mean Sq F value    Pr(>F)
## uniyear                   1   82.2   82.22  6.8964   0.00888 **
## country                   1   23.6   23.63  1.9823   0.15972
## eduprog3                  2 1302.4  651.21 54.6250 < 2.2e-16 ***
## uniyear:country           1    0.0    0.01  0.0006   0.98053
## uniyear:eduprog3          2   57.1   28.56  2.3956   0.09208 .
## country:eduprog3          2  314.8  157.42 13.2050 2.512e-06 ***
```

```
## uniyear:country:eduprog3   2  105.6   52.79  4.4279   0.01237 *
## Residuals                544 6485.3   11.92
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Analysis of the models (financial knowledge vs. study year) in the subgroups (education type × country) gives inconclusive results. For three groups (SSHA students in Poland and Czech Republic and EBMF students in Czech Republic) it is rather certain that there are no association between financial knowledge and study year. For the others (EBMF in Poland and STEM in both Poland and Czech Republic) the assocaition is very close to being significant (see the outputs below). It means that we rather can not rule out that there may be a positive association between financial knowledge and study year in amongst Polish EBMF studenst and Czech STEM students. Surprisngly enough we also can not rule out that there is a negative association between the variables in the group of Polish STEM students.

```
## ######
## GROUP : EBMF in CZ
## ######
##
## Call:
## lm(formula = ngfinance ~ uniyear, data = data, subset = data$eduprog3 ==
##     edu & data$country == cntry)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -11.880  -1.880   1.058   2.120   7.058
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.0670     1.2893   0.828   0.4101
## uniyear       0.9376     0.5473   1.713   0.0901 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.131 on 91 degrees of freedom
##   (4 observations deleted due to missingness)
## Multiple R-squared:  0.03124,    Adjusted R-squared:  0.02059
## F-statistic: 2.934 on 1 and 91 DF,  p-value: 0.09013
##
## ######
## GROUP : EBMF in PL
## ######
##
## Call:
## lm(formula = ngfinance ~ uniyear, data = data, subset = data$eduprog3 ==
##     edu & data$country == cntry)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -14.285  -2.285   1.089   3.089   7.089
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.1623     1.6364   1.321   0.1895
## uniyear       1.3742     0.6936   1.981   0.0504 .
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.831 on 97 degrees of freedom
##   (10 observations deleted due to missingness)
## Multiple R-squared:  0.03889,    Adjusted R-squared:  0.02898
## F-statistic: 3.925 on 1 and 97 DF,  p-value: 0.05041
##
## ######
## GROUP : SSHA in CZ
## ######
##
## Call:
## lm(formula = ngfinance ~ uniyear, data = data, subset = data$eduprog3 ==
##     edu & data$country == cntry)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7.0533 -1.6393 -0.8813  2.7747  7.1187
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   1.3973     0.8185   1.707   0.0902 .
## uniyear      -0.1720     0.3801  -0.452   0.6517
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.938 on 130 degrees of freedom
##   (20 observations deleted due to missingness)
## Multiple R-squared:  0.001572,   Adjusted R-squared:  -0.006108
## F-statistic: 0.2047 on 1 and 130 DF,  p-value: 0.6517
##
## ######
## GROUP : SSHA in PL
## ######
##
## Call:
## lm(formula = ngfinance ~ uniyear, data = data, subset = data$eduprog3 ==
##     edu & data$country == cntry)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8.8021 -2.8021  0.2632  2.7958  8.7958
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -1.3284     0.9729  -1.365    0.176
## uniyear       0.5326     0.3737   1.425    0.158
##
## Residual standard error: 4.047 on 79 degrees of freedom
##   (10 observations deleted due to missingness)
## Multiple R-squared:  0.02507,    Adjusted R-squared:  0.01273
## F-statistic: 2.031 on 1 and 79 DF,  p-value: 0.158
##
```

```
## ######
## GROUP : STEM in CZ
## ######
##
## Call:
## lm(formula = ngfinance ~ uniyear, data = data, subset = data$eduprog3 ==
##     edu & data$country == cntry)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -11.670  -2.025   0.330   2.330   5.975
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -1.2645     2.1374  -0.592   0.5570
## uniyear       1.6448     0.8236   1.997   0.0516 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.316 on 47 degrees of freedom
##   (12 observations deleted due to missingness)
## Multiple R-squared:  0.07822,    Adjusted R-squared:  0.0586
## F-statistic: 3.988 on 1 and 47 DF,  p-value: 0.05163
##
## ######
## GROUP : STEM in PL
## ######
##
## Call:
## lm(formula = ngfinance ~ uniyear, data = data, subset = data$eduprog3 ==
##     edu & data$country == cntry)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -10.1555  -2.1555  -0.1555   2.7990   5.8445
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   4.2465     1.2725   3.337  0.00119 **
## uniyear      -1.0455     0.5598  -1.867  0.06476 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.517 on 100 degrees of freedom
##   (29 observations deleted due to missingness)
## Multiple R-squared:  0.0337, Adjusted R-squared:  0.02404
## F-statistic: 3.488 on 1 and 100 DF,  p-value: 0.06476
```