

# Notes on the estimation of high-dimensional FE with variable returns to ability.

Ekaterina Roshchina

March 20, 2016

## 1 Proposed procedure

Model to be estimated:

$$\log\_earn_{ijart} = \mu_{rt} + \delta_t \alpha_i + \theta_a + \gamma_{jt} + \varepsilon_{iarjt} \quad (1)$$

Algorithm:

1. Initialize the values of  $\delta_t^{(0)}, \alpha_i^{(0)}$ .
2. At iteration  $k$ , estimate  $\mu_{rt}^{(k)}, \theta_a^{(k)}, \gamma_{jt}^{(k)}$  by OLS given the values  $\delta_t^{(k-1)}, \alpha_i^{(k-1)}$ . Do it in two steps:
  - (a) Estimate  $\mu_{rt}^{(k)}$  given  $\gamma_{jt}^{(k-1)}$  and  $\delta_t^{(k-1)} \alpha_i^{(k-1)}$ .
  - (b) Estimate  $\gamma_{jt}^{(k)}$  and  $\theta_a^{(k)}$  given  $\mu_{rt}^{(k)}$  and  $\delta_t^{(k-1)} \alpha_i^{(k-1)}$ .
3. Renew the values for  $\delta_t^{(k)}, \alpha_i^{(k)}$  using the following expressions:

$$\alpha_i^{(k)} = \sum_t \tilde{\varepsilon}_{it}^{(k)} \delta_t^{(k-1)} / \sum_t \left( \delta_t^{(k-1)} \right)^2, \quad (2)$$

$$\delta_t^{(k)} = \sum_i \tilde{\varepsilon}_{it}^{(k)} \alpha_i^{(k-1)} / \sum_i \left( \alpha_i^{(k-1)} \right)^2, \quad (3)$$

where  $\tilde{\varepsilon}_{it}^{(k)} = \log\_earn_{ijart} - \mu_{rt}^{(k)} - \theta_a^{(k)} - \gamma_{jt}^{(k)}$ .

4. Normalize  $\delta_1$  at year 1 to be 1.
5. Iterate steps 2-3 till convergence.
  - Convergence criterion: residual sum of squares of the model is not changing from  $k$  to  $k - 1$ .  
Current tolerance: 1e-4

- Convergence check: Coefficients at  $\delta_t^k \alpha_i^k$ ,  $\mu_{rt}^{(k)}$  and  $\gamma_{jt}^{(k)}$  should equal to 1

This procedure mirrors the suggestion of ? on pp. 429-430. The basic intuition comes from the fact that the estimates should minimize the NLS objective function  $Q_n$ :

$$Q_n = \sum_i \sum_t (\log\_earn_{ijart} - \mu_{rt} - \delta_t \alpha_i - \theta_a - \gamma_{jt})^2 \quad (4)$$

However, since this is infeasible, at each step only low-dimension coefficients are estimated, and then the person fixed effects are recovered using the first order conditions for estimating  $\delta_t$  and  $\alpha_i$ . These FOCs give the expressions for updating. What is required for the procedure to work is that  $Q_n^{(k)}$  decreases at each iteration, i.e. it is a contraction mapping. I do not have a formal proof for this case, though in the empirical implementation  $Q_n^{(k)}$  does decrease at each iteration.

FOCs for the estimates of  $\delta_t$  and  $\alpha_i$ :

$$\sum_t (\log\_earn_{ijart} - \mu_{rt} - \delta_t \alpha_i - \theta_a - \gamma_{jt}) \alpha_i = 0 \quad (\alpha_i)$$

$$\sum_i (\log\_earn_{ijart} - \mu_{rt} - \delta_t \alpha_i - \theta_a - \gamma_{jt}) \delta_t = 0 \quad (\delta_t)$$

## 1.1 Standard errors

Standard errors are implemented using wild bootstrap, as in ?.

Implementation is based on the guidelines from ?.

Steps:

1. Predict  $\widehat{\log\_earn}_{ijart}$  and  $\hat{\epsilon}_{iarjt}$ .
2. Draw a sample of residuals (with replacement) from  $\hat{\epsilon}_{iarjt}$
3. Construct a bootstrap sample as follows:

$$\log\_earn_{ijart}^* = \widehat{\log\_earn}_{ijart} + f(\hat{\epsilon}_{ijart}^*) v_{ijart}^*, \quad (5)$$

where  $f(\hat{\epsilon}_{ijart}^*)$  is simply  $\hat{\epsilon}_{ijart}^*$  (resampled residuals), and

$$v_{ijart}^* = \begin{cases} -0.5(\sqrt{5} - 1) & \text{with probability } (\sqrt{5} + 1)/(2\sqrt{5}) \\ -0.5(\sqrt{5} + 1) & \text{with probability } (\sqrt{5} - 1)/(2\sqrt{5}) \end{cases} \quad (6)$$

## 2 Fixed effects: `felsdvreg` vs. `reghdfe`

### 2.1 Differences between `felsdvreg` vs. `reghdfe`

Normalization used by `reghdfe`:

- Mean of each fixed effect is 0, i.e.  $\frac{1}{N} \sum_i \alpha_i = 0$ ,  $\frac{1}{N} \sum_i \mu_{rt} = 0$ ,  $\frac{1}{N} \sum_i \gamma_{jt} = 0$ , where  $N$  is the total number of observations. For industry and region fixed effects that translates into  $\frac{1}{N} \sum_{rt} N_{rt} \mu_{rt} = 0$ , where  $N_{rt}$  is the number of observations in  $rt$  cell.

Normalization used by `felsdvreg`:

- Normalization for industry-year effect  $\gamma_{jt}$  is chosen manually, as these effects are not estimated by `felsdvreg`.
- Normalization for region-year effect is based on mobility groups. `felsdvreg` splits all observations on groups connected by worker mobility (0 stands for no movers group, 1 is always the largest group in the data etc.). Region-year effect (or “firm” effect in the usual terminology) is set to 0 for the first region-year observation in each group.

Similarities between the two procedures:

- Estimates for any variables, which are not in the fixed effects (i.e. returns to age here) are *exactly* the same.

Difference between the number of region-year estimation produced by `felsdvreg` and by `reghdfe`:

- Both `felsdvreg` and `reghdfe` use the same sample to estimate the model and yield the same estimates for  $\theta_a$ . In other words, `e(sample)` marks the same set in Stata for both estimates
- Final estimation sample for `reghdfe` must have at least 2 observations per each group for which fixed effects are estimated. This can be achieved using the following algorithm:
  1. For each fixed effects variable, calculate the number of observations group in the current sample
  2. Mark any observations with less than 2 observations per group as not in the estimation sample
  3. Repeat steps 1–2 till there are no observations to be dropped.

- There are 8 mmc-year cells which have more than 2 observations in the data, but get dropped by `reghdfe`:

	mmc_year	mmc	year	n_obs_mmc_year_data
128.	128	12003	1990	2
129.	129	12003	1991	3
416.	416	13011	2001	2
478.	478	14004	1994	2
1034.	1034	16004	1987	2
1617.	1617	22012	1994	2
4122.	4122	27007	2004	4
11280.	11280	51008	1989	2

- In all cases except mmc\_year 1034 (mmc 16004 in 1987), this happens because of the individual observations which get dropped, because these people have fewer than 2 observations. Once all people with 1 observations are dropped, there is only 1 observation per mmc-year cell.

	indiv	subs_ibge_year	mmc_year	n_obs_indiv_data
1.	594277	118	128	10
2.	952024	116	128	1
3.	594277	142	129	10
4.	952023	123	129	1
5.	952165	123	129	1
6.	1247016	374	416	1
7.	2106647	382	416	17
8.	307971	196	478	8
9.	1073372	196	478	1
10.	263675	27	1034	6
11.	779331	30	1034	2
12.	319010	210	1617	20
13.	1080345	195	1617	1

14.		430592	433	4122	7	
15.		2166342	453	4122	1	
16.		2166343	453	4122	1	
17.		2166346	453	4122	1	
+-----+						
18.		649923	96	11280	3	
19.		777379	73	11280	1	
+-----+						

- The case of mmc-year 1034 is similar: Person 779331 in year 1988 gets dropped because this is an only observation for mmc-year 1035. Mmc-year 1034 still has 2 observation per group, but then person 779331 get dropped altogether, because now there is only 1 observation for him. Which also leaves only 1 observation for mmc-year 103, and it's excluded from the estimation sample as well.

+-----+						
		indiv	year	mmc_year	n_obs_mmc_year_data	
+-----+						
1.		263675	1987	1034	2	
2.		263675	1991	1036	8	
3.		263675	1992	1037	5	
4.		263675	1993	1038	4	
5.		263675	1994	1039	7	
6.		263675	1995	1040	8	
+-----+						
7.		779331	1987	1034	2	
8.		779331	1988	1035	1	
+-----+						

## 2.2 Algorithm to re-normalize results of `reghdfe` to be the same as `felsdvreg`

1. **Industry-year FE.** Denote by  $\gamma_{0t}$  the reference industry within each year (omitted group). Also, denote by  $\tilde{\gamma}_{jt}$  the new, re-normalized estimates, and by  $\hat{\gamma}_{jt}$  the original `reghdfe` estimates. Then, the modified estimates are:

$$\tilde{\gamma}_{jt} = \hat{\gamma}_{jt} - \hat{\gamma}_{0t} \quad (7)$$

2. **Region-year FE.** Denote by  $\mu_{0t}$  the reference region-year group within each mobility group (omitted group). Then, the modifies estimates are:

$$\tilde{\mu}_{jt} = \hat{\mu}_{rt} - \hat{\mu}_{0t} + \hat{\gamma}_{0t} - \frac{1}{N} \sum_t N_t \hat{\gamma}_{0t} \quad (8)$$

3. **Individual FE.** Denote by  $\hat{b}_1$  the constant in the regression of log earnings on age categories and three fixed effects estimates by `reghdfe`, and by  $\hat{b}_2$  the constant in the regression of

log earnings on age categories and three fixed effects estimates by `felsdvreg`.

$$\tilde{\alpha}_i = \hat{\alpha}_i + \hat{b}_1 - +\hat{b}_2 + \hat{\mu}_{0t} + \frac{1}{N} \sum_t N_t \hat{\gamma}_{0t} \quad (9)$$

In case of varying return to ability, renormalized individual fixed effects can be obtained as follows:

$$\tilde{\alpha}_i = \hat{\alpha}_i + \frac{1}{\hat{\delta}_t} \left( \hat{b}_1 - +\hat{b}_2 + \hat{\mu}_{0t} + \frac{1}{N} \sum_t N_t \hat{\gamma}_{0t} \right) \quad (10)$$

Caveats:

- `reghdfe` and `felsdvreg` yield estimates for different samples, even though they use the same samples to estimate the model. `reghdfe` operates on the sample for which there are at least 2 observation for each individual, each industry-year category and each region-year category. In the data data, 3% of individuals for whom `felsdvreg` identifies individual fixed effects having missing individual fixed effect in the `reghdfe` routine. `felsdvreg` used the same sample in the estimation, but then constructs fixed effects for observation for outside of this sample (excluding observations which are in the 0 mobility group), so that residual for these observations is set to 0.
- Because of the fact above, `felsdvreg` occasionally can have region-year reference categories for which the corresponding `reghdfe` estimates are missing. For now, I omitted such observations from the re-normalization.

### 3 Implementation: iterative procedure with non-linear FE

Do-files description:

- `est_fe_actual_data_cp_as_is_v2.do`  
Estimates standard fixed effects model using `felsdvreg` and `reghdfe`.
- `est_fe_actual_data_cp_renormalize.do`  
Normalizes the estimates from `reghdfe` to be comparable with `felsdvreg` and saves the results.
- `est_nlfe_v14_actual_data.do`  
Estimates the model with variable returns to ability.
- `est_nlfe_v14_bootstrap.do`  
Runs bootstrap for the model with variable returns to ability.
- `est_nlfe_v15_bootstrap_collect.do`  
Calculates bootstrap standard errors and saves all the results in one file per estimate type.

Output description:

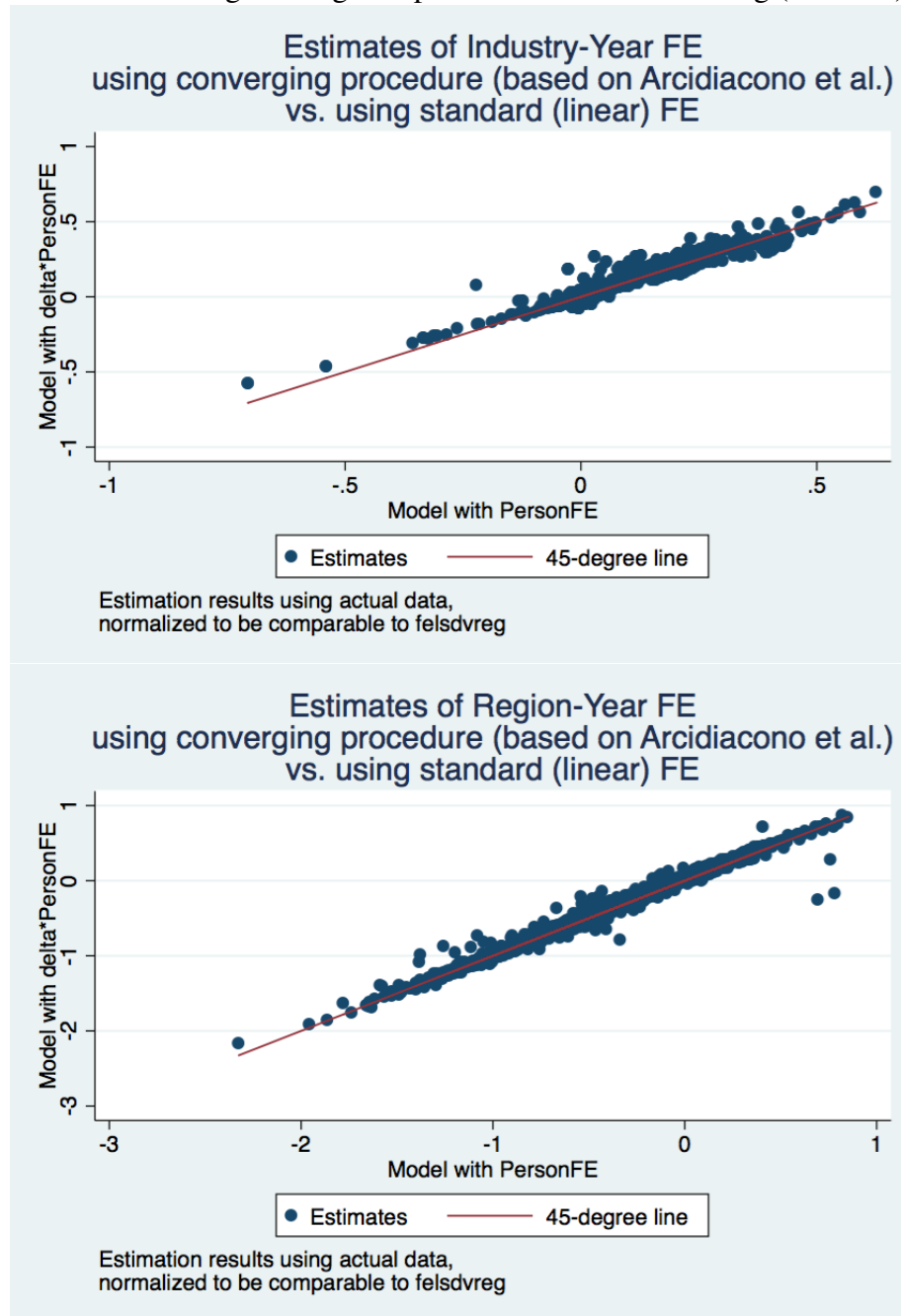
- `RegionYearFE_all_est_v2_withse_v2.dta`  
Variables:
  - `year`
  - `mmc`
  - `mmc_year`
  - `RegionYearFE1` Estimate of Region-Year FE using `reghdfe`
  - `RegionYearFE2` Estimate of Region-Year FE using `felsdvreg`
  - `RegionYearFE1_renorm` Estimate of Industry-Year FE using `reghdfe`, renormalized to be comparable with `felsdvreg`
  - `RegionYearFE_nlhdfc` Estimate of Region-Year FE using the model with the variable returns to ability
  - `RegionYearFE_nlhdfc_renorm` Estimate of Region-Year FE using the model with the variable returns to ability, renormalized to be comparable with `felsdvreg`
  - `B_effective` Number of bootstrap iterations (500)
  - `RegionYearFE_nl_se` S.e. estimate of Region-Year FE using the model with the variable returns to ability
  - `RegionYearFE_nl_renorm_se` S.e. estimate of Region-Year FE using the model with the variable returns to ability, renormalized to be comparable with `felsdvreg`
- `IndustryYearFE_all_est_v2_withse_v2.dta`  
Variables:

- year
  - subs\_ibge
  - subs\_ibge\_year
  - IndustryYearFE1 Estimate of Industry-Year FE using `reghdfe`
  - IndustryYearFE2 Estimate of Industry-Year FE using `felstdvreg`
  - IndustryYearFE1\_renorm Estimate of Industry-Year FE using `reghdfe`, renormalized to be comparable with `felstdvreg`
  - IndustryYearFE\_nlhdfc Estimate of Industry-Year FE using the model with the variable returns to ability
  - IndustryYearFE\_nlhdfc\_renorm Estimate of Industry-Year FE using the model with the variable returns to ability, renormalized to be comparable with `felstdvreg`
  - B\_effective Number of bootstrap iterations (500)
  - IndustryYearFE\_nl\_se S.e. estimate of Industry-Year FE using the model with the variable returns to ability
  - IndustryYearFE\_nl\_renorm\_se S.e. estimate of Industry-Year FE using the model with the variable returns to ability, renormalized to be comparable with `felstdvreg`
- `delta_nlhdfc_all_est_v2_withse_v2.dta`  
Variables:
    - year
    - delta\_nlhdfc Estimate of the return to ability using the model with the variable returns to ability
    - B\_effective Number of bootstrap iterations (500)
    - delta\_nl\_se S.e. for the estimate of the return to ability using the model with the variable returns to ability
- `IndFE_all_est_v2.dta`  
Variables:
    - indiv
    - PersonFE1 Estimate of individual FE using `reghdfe`
    - PersonFE2 Estimate of individual FE using `felstdvreg`
    - PersonFE\_nlhdfc Estimate of individual FE using the model with the variable returns to ability
    - PersonFE1\_renorm Estimate of individual FE using `reghdfe` renormalized to be comparable with `felstdvreg`
    - PersonFE\_nlhdfc\_renorm Estimate of individual FE using the model with the variable returns to ability renormalized to be comparable with `felstdvreg`

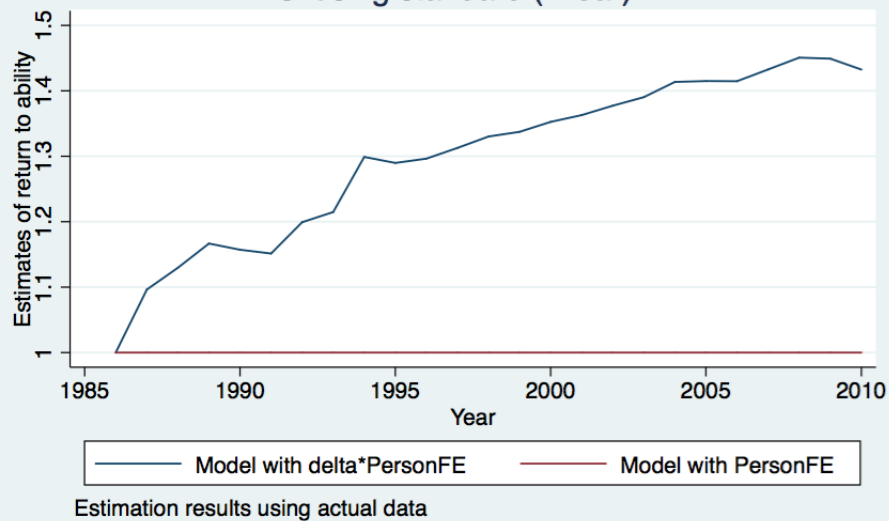


### 3.1 Results comparison: constant vs. varying returns to individual effects

Comparison of results using convergence procedure with results using (standard) linear FE.



Estimates of delta (fixed at 1 for linear case)  
using converging procedure (based on Arcidiacono et al.)  
vs. using standard (linear) FE



Estimates of Person FE  
using converging procedure (based on Arcidiacono et al.)  
vs. using standard (linear) FE

