Basics of REGHDFE

June 26, 2022

1 Basics of reghdfe

We are interested in the estimation of a linear model such as

$$y = \mathbf{X}\beta + \mathbf{D}\alpha + \epsilon \tag{1}$$

where $\mathbf{D} = [\mathbf{D}_1\ \mathbf{D}_2\ ...\ \mathbf{D}_F]$ and the generic $\mathbf{D}_i$ is a matrix of dummy variables associated with an indicator variable.

Consider the following dataset:

[1]:
```
estimates clear
use fakedata, clear
sum
list in 1/10
```

```
    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
           i |        100       12.48    5.292419          1         20
           j |        100        8.37    4.409941          1         15
           t |        100        3.76    2.283538          1          9
           y |        100    -1.92123    10.76019    -28.771     27.271
          x1 |        100         .32    2.898554         -5          5
-------------+---------------------------------------------------------
          x2 |        100         .36    2.976406         -5          5
         zi1 |        100    .4886572    .2834865   .1086679   .8948932
```

```
     +-----------------------------------------+
     | i    j    t         y    x1   x2        zi1 |
     |-----------------------------------------|
  1. | 1    1    1   -12.941    1   -2   .1369841 |
  2. | 2    1    1   -13.734    0    1   .6432207 |
  3. | 2    1    2   -11.393   -4    1   .6432207 |
```

```
  4. | 3    2    1      5.792     3     3    .6047949 |
  5. | 3    2    2      3.198    -5     1    .6047949 |
     |-----------------------------------------------|
  6. | 4    2    1    -15.984    -3    -2    .1086679 |
  7. | 4    2    2     -1.193     4     4    .1086679 |
  8. | 4    2    3    -15.067    -4     0    .1086679 |
  9. | 4    2    4    -10.596     3    -2    .1086679 |
 10. | 5    2    1     -4.777     5     0    .8714491 |
     +-----------------------------------------------+
```

2 Regression with one fixed effect (F=1)

There are basically three ways to run a regression with one fixed effect in official Stata!

[2]:
```
qui regress y x1 x2 i.i
estimates store reg_1
qui areg y x1 x2, absorb(i)
estimates store areg_1
qui xtset i
qui xtreg y x1 x2, fe
estimates store xtreg_1
```

2.1 Estimation with reghdfe

[3]:
```
which reghdfe
qui reghdfe y x1 x2 i.i
estimates store reghdfe_1a
qui reghdfe y x1 x2, absorb(i)
estimates store reghdfe_1b
```

```
C:\Users\eeu257\ado\plus\r\reghdfe.ado
*! version 6.12.2 02Nov2021
```

[4]:
```
estimates table *_1 reghdfe_1a reghdfe_1b, keep(x1 x2) b(%7.4f) se(%7.4f)
  stats(N r2 r2_a)
```

```
----------------------------------------------------------------
    Variable |  reg_1     areg_1     xtreg_1    regh~1a    regh~1b
-------------+--------------------------------------------------
          x1 |  1.0659     1.0659     1.0659     1.0659     1.0659
             |  0.2885     0.2885     0.2885     0.2885     0.2885
```

```
           x2 | -0.6755   -0.6755   -0.6755   -0.6755   -0.6755
              |  0.2863    0.2863    0.2863    0.2863    0.2863
--------------+---------------------------------------------------
            N |     100       100       100       100        97
           r2 |  0.5832    0.5832    0.1990    0.5832    0.5777
         r2_a |  0.4710    0.4710   -0.0166    0.4710    0.4803
------------------------------------------------------------------
                                                      legend: b/se
```

Coefficients and ses are identical in all regressions but… - **xtreg** reports the "within" R^2 and $AdjR^2$ - **reghdfe** with **absorb** option reports less observations - it drops singletons! - Dropping singletons affects calculation of R^2 and $AdjR^2$

2.2 What if the robust option is included?

[5]:
```
qui regress y x1 x2 i.i, vce(robust)
estimates store reg_2a
qui areg y x1 x2, absorb(i) vce(robust)
estimates store areg_2a
qui xtreg y x1 x2, fe vce(robust)
estimates store xtreg_2a
qui reghdfe y x1 x2, absorb(i) vce(robust)
estimates store reghdfe_2a
estimates table *_2a, keep(x1 x2) b(%7.4f) se(%7.4f) stats(N)
```

```
--------------------------------------------------------
    Variable | reg_2a    areg_2a   xtre~2a   regh~2a
-------------+------------------------------------------
          x1 |  1.0659    1.0659    1.0659    1.0659
             |  0.2906    0.2906    0.2956    0.2862
          x2 | -0.6755   -0.6755   -0.6755   -0.6755
             |  0.3025    0.3025    0.3148    0.2979
-------------+------------------------------------------
           N |     100       100       100        97
--------------------------------------------------------
                                            legend: b/se
```

- **regress** and **areg** produce the same results
- **xtreg** produces different clustered ses

- **reghdfe** also produces ses different from all other

What is going on?

- **xtreg** assumes that the data are clustered in **i**. With **xtreg** the option **vce(robust)** is the same as **vce(cluster i)**
- **reghdfe** produces different results because it drops singletons by default!
- Adding singletons biases your ses! If you want to keep singletons use option **keepsingletons**

2.3 What if the cluster option is included?

[6]:
```
qui regress y x1 x2 i.i, vce(cluster i)
estimates store reg_2b
qui areg y x1 x2, absorb(i)  vce(cluster i)
estimates store areg_2b
qui xtreg y x1 x2, fe vce(cluster i)
estimates store xtreg_2b
qui reghdfe y x1 x2, absorb(i)  vce(cluster i)
estimates store reghdfe_2b
qui reghdfe y x1 x2, absorb(i)  vce(cluster i) keepsingletons
estimates store reghdfe_2ba

estimates table *_2b *_2ba, keep(x1 x2) b(%7.4f) se(%7.4f) stats(N)
```

```
WARNING: Singleton observations not dropped; statistical significance is biased
> (link)
```

```
----------------------------------------------------------------
    Variable | reg_2b    areg_2b   xtre~2b   regh~2b   reghd~a
-------------+--------------------------------------------------
          x1 |  1.0659    1.0659    1.0659    1.0659    1.0659
             |  0.3296    0.3296    0.2956    0.2971    0.2956
          x2 | -0.6755   -0.6755   -0.6755   -0.6755   -0.6755
             |  0.3511    0.3511    0.3148    0.3164    0.3148
-------------+--------------------------------------------------
           N |     100       100       100        97       100
----------------------------------------------------------------
                                                    legend: b/se
```

- **regress** and **areg** produce the same results - they adjust the dof by the number of coefficients in the fes
- **xtreg** does not count the fes in the dof - this is appropriate if the fixed effects are nested within clusters
- **xtreg** produces the same results as with the **vce(robust)** option
- since the fe is nested within the cluster **reghdfe** (with option **keepsingleton**) produces the same ses as **xtreg**
- you can force **xtreg** to use the same correction as **areg** (option **dfadj**)

Now we cluster on the variable *j*

[7]:
```
qui regress y x1 x2 i.i, vce(cluster j)
estimates store reg_2c
qui areg y x1 x2, absorb(i)  vce(cluster j)
estimates store areg_2c
*qui xtreg y x1 x2, fe vce(cluster j)
*estimates store xtreg_2c
qui reghdfe y x1 x2, absorb(i)  vce(cluster j)
estimates store reghdfe_2c
qui reghdfe y x1 x2, absorb(i)  vce(cluster j) keepsingletons
estimates store reghdfe_2ca

estimates table *_2c *_2ca, keep(x1 x2) b(%7.4f) se(%7.4f) stats(N)
```

```
WARNING: Singleton observations not dropped; statistical significance is biased
> (link)
```

```
------------------------------------------------------
    Variable | reg_2c    areg_2c   regh~2c   reghd~a
-------------+----------------------------------------
          x1 |  1.0659    1.0659    1.0659    1.0659
             |  0.2562    0.2562    0.2523    0.2562
          x2 | -0.6755   -0.6755   -0.6755   -0.6755
             |  0.1972    0.1972    0.1942    0.1972
-------------+----------------------------------------
           N |     100       100        97       100
------------------------------------------------------
```

```
                                          legend: b/se
```

- **xtreg** fails to estimate
- now **reghdfe** produces the same results as **regress** and **areg** (if we keep singletons)

2.4 Other reasons why reghdfe is better!

[8]:
```
clear all
use data1fe
```

```
(National Longitudinal Survey.  Young Women 14-26 years of age in 1968)
```

This is a subset of the dataset *nlswork*.

[9]:
```
%browse
```

```
     +-----------------------------------------------------------------+
     | idcode   year   birth_yr   age    race     tenure     ln_wage |
     |-----------------------------------------------------------------|
  1. |      1     70         51    18   black   .0833333   1.451214 |
  2. |      1     71         51    19   black   .0833333    1.02862 |
  3. |      1     72         51    20   black   .9166667   1.589977 |
  4. |      1     73         51    21   black   .0833333   1.780273 |
  5. |      1     75         51    23   black   .1666667   1.777012 |
     |-----------------------------------------------------------------|
  6. |      1     77         51    25   black        1.5   1.778681 |
  7. |      1     78         51    26   black   .0833333   2.493976 |
  8. |      1     80         51    28   black   1.833333   2.551715 |
  9. |      1     83         51    31   black   .6666667   2.420261 |
 10. |      1     85         51    33   black   1.916667   2.614172 |
     |-----------------------------------------------------------------|
 11. |      1     87         51    35   black   3.916667   2.536374 |
 12. |      2     71         51    19   black        .25   1.360348 |
 13. |      2     72         51    20   black          1   1.206198 |
 14. |      2     73         51    21   black   .3333333   1.549883 |
 15. |      2     75         51    23   black   .6666667   1.832581 |
     |-----------------------------------------------------------------|
 16. |      2     77         51    25   black   2.666667   1.726721 |
 17. |      2     78         51    26   black   3.666667    1.68991 |
 18. |      2     80         51    28   black   5.583333   1.726964 |
 19. |      2     82         51    30   black   7.666667   1.808289 |
 20. |      2     83         51    31   black   8.583333   1.863417 |
     |-----------------------------------------------------------------|
 21. |      2     85         51    33   black   1.833333   1.789367 |
 22. |      2     87         51    35   black       3.75    1.84653 |
 23. |      3     68         45    22   black          0   1.493561 |
```

24.	3	69	45	23	black	.3333333	1.702528
25.	3	70	45	24	black	.5	1.451214
26.	3	71	45	25	black	1.416667	1.54742
27.	3	72	45	26	black	2.416667	1.607294
28.	3	73	45	27	black	3.333333	1.597267
29.	3	75	45	29	black	.4166667	1.53585
30.	3	77	45	31	black	2.416667	1.622841
31.	3	78	45	32	black	3.416667	1.566635
32.	3	80	45	34	black	5.333333	1.559723
33.	3	82	45	36	black	7.333333	1.603419
34.	3	83	45	37	black	8.333333	1.614229
35.	3	85	45	39	black	10.33333	1.730799
36.	3	87	45	41	black	.4166667	1.525765
37.	3	88	45	42	black	1.25	1.612777
38.	4	70	45	24	white	1.416667	2.2885
39.	4	71	45	25	white	2.416667	2.375578
40.	4	72	45	26	white	3.416667	2.413923
41.	4	73	45	27	white	3.75	2.280939
42.	4	75	45	29	white	3.75	2.258814
43.	4	80	45	34	white	.3333333	1.476236
44.	4	82	45	36	white	2.416667	1.280933
45.	4	83	45	37	white	3.416667	1.515855
46.	4	85	45	39	white	5.416667	1.93017
47.	4	87	45	41	white	.3333333	1.919034
48.	5	68	45	22	white	0	1.627093
49.	5	69	45	23	white	.8333333	1.787686
50.	5	70	45	24	white	1.916667	1.820858
51.	5	71	45	25	white	2.916667	1.858522
52.	5	72	45	26	white	.6666667	1.979301
53.	5	73	45	27	white	1.666667	1.990412
54.	5	75	45	29	white	.3333333	1.585505
55.	5	77	45	31	white	1.75	1.937521
56.	5	78	45	32	white	.3333333	2.070492
57.	5	80	45	34	white	1.833333	1.830269
58.	5	82	45	36	white	3.333333	1.847272
59.	6	68	46	21	white	.1666667	1.521732
60.	6	70	46	23	white	1	1.479384
61.	6	71	46	24	white	.4166667	1.518572
62.	6	72	46	25	white	1.416667	1.607294
63.	6	73	46	26	white	2.333333	1.809742

64.	6	75	46	28	white	4.416667	1.853972
65.	6	77	46	30	white	6.416667	1.96311
66.	6	78	46	31	white	7.416667	1.982733
67.	6	80	46	33	white	9.416667	1.846798
68.	6	82	46	35	white	11.41667	1.814825
69.	6	83	46	36	white	12.41667	1.919913
70.	6	85	46	38	white	14.41667	1.958377
71.	6	87	46	40	white	16.41667	2.007068
72.	7	69	49	19	white	1.666667	1.490434
73.	7	73	49	23	white	4.833333	1.454573
74.	7	87	49	37	white	.8333333	.4733421
75.	9	70	51	18	white	.6666667	1.472237
76.	9	71	51	19	white	1.583333	1.717023
77.	9	72	51	20	white	2.5	1.747242
78.	9	73	51	21	white	3.583333	1.799792
79.	9	75	51	23	white	5.583333	2.017152
80.	9	77	51	25	white	7.583333	2.091364
81.	9	78	51	26	white	8.583333	2.114099
82.	9	80	51	28	white	10.5	2.113776
83.	9	82	51	30	white	12.58333	2.312535
84.	9	83	51	31	white	13.5	2.34858
85.	9	85	51	33	white	15.5	2.373487
86.	9	87	51	35	white	17.5	2.368899
87.	10	69	51	17	white	.4166667	1.361601
88.	10	70	51	18	white	1.416667	1.461484
89.	10	71	51	19	white	2.416667	1.611663
90.	10	72	51	20	white	3.25	1.301507
91.	10	75	51	23	white	.8333333	1.391349
92.	10	77	51	25	white	0	1.321256
93.	10	78	51	26	white	.0833333	1.416566
94.	10	80	51	28	white	.4166667	1.275272
95.	10	82	51	30	white	.0833333	.7974494
96.	12	87	47	39	white	12.83333	3.000736
97.	12	88	47	40	white	14.16667	2.845265
98.	13	70	47	22	white	.5833333	1.952854
99.	13	71	47	23	white	1.416667	1.954463
100.	13	73	47	25	white	.1666667	1.86433
101.	13	75	47	27	white	2.166667	2.094945
102.	13	78	47	30	white	.9166667	2.125834
103.	13	82	47	34	white	1	2.119863

104.	13	83	47	35	white	2	2.667868
105.	13	85	47	37	white	2.166667	3.579129
106.	13	87	47	39	white	4	1.678877
107.	13	88	47	40	white	5.5	2.57137
108.	14	87	47	39	white	.8333333	2.143405
109.	14	88	47	40	white	2.25	2.047121
110.	15	77	48	28	white	2	2.205023
111.	15	78	48	29	white	2.833333	2.340595
112.	15	80	48	31	white	.0833333	2.383516
113.	15	82	48	33	white	2.083333	2.539237
114.	15	83	48	34	white	3	2.485547
115.	15	85	48	36	white	5	2.307946
116.	15	87	48	38	white	7	2.813745
117.	15	88	48	39	white	8.416667	2.82111
118.	16	70	48	21	white	.5	2.043247
119.	16	71	48	22	white	.6666667	1.984131
120.	16	72	48	23	white	1.666667	2.011328
121.	16	73	48	24	white	2.833333	2.087474
122.	16	75	48	26	white	.5	1.832581
123.	16	77	48	28	white	2.416667	1.93536
124.	16	78	48	29	white	3.416667	2.01862
125.	16	80	48	31	white	5.416667	1.979646
126.	16	82	48	33	white	7.416667	2.128231
127.	16	83	48	34	white	8.416667	2.171384
128.	16	85	48	36	white	10.5	2.253929
129.	16	87	48	38	white	12.5	2.64418
130.	17	70	48	21	white	.5	2.000029
131.	17	71	48	22	white	1.416667	1.954463
132.	17	72	48	23	white	2.333333	2.083182
133.	17	73	48	24	white	3.416667	2.647089
134.	17	77	48	28	white	6.416667	2.039102
135.	17	87	48	38	white	3.333333	2.372024
136.	18	77	48	28	white	.9166667	1.237874
137.	18	85	48	36	white	4.333333	1.538907
138.	18	87	48	38	white	6.333333	1.629306
139.	19	70	48	21	white	.5	2.01878
140.	19	71	48	22	white	1.5	2.042001
141.	19	72	48	23	white	2.416667	1.773027
142.	19	73	48	24	white	2.916667	1.798163
143.	19	75	48	26	white	1.75	1.932793

144.	19	78	48	29	white	.9166667	1.780994
145.	19	80	48	31	white	2.833333	1.704118
146.	19	82	48	33	white	4.833333	1.811562
147.	19	83	48	34	white	.1666667	2.139105
148.	19	85	48	36	white	2.166667	2.192834
149.	19	87	48	38	white	4.166667	2.284871
150.	20	70	48	21	white	.5	2.01878
151.	20	71	48	22	white	1.5	2.081666
152.	20	72	48	23	white	.3333333	2.117261
153.	20	73	48	24	white	1.416667	2.099896
154.	20	75	48	26	white	3.416667	2.082393
155.	20	77	48	28	white	5.416667	2.10058
156.	20	78	48	29	white	6.416667	1.990396
157.	20	80	48	31	white	2	1.958695
158.	20	82	48	33	white	3.583333	1.927315
159.	20	83	48	34	white	.75	2.068818
160.	20	85	48	36	white	1.333333	2.192834
161.	20	87	48	38	white	3.25	2.218913
162.	20	88	48	39	white	4.666667	2.268184
163.	21	70	48	21	white	.3333333	1.907555
164.	21	72	48	23	white	1.75	2.208345
165.	21	73	48	24	white	2.75	2.194083
166.	21	75	48	26	white	1.166667	1.910543
167.	21	85	48	36	white	10	.9855224
168.	22	69	47	21	white	.4166667	1.949388
169.	22	70	47	22	white	1.416667	1.971228
170.	22	71	47	23	white	2.416667	2.042001
171.	22	72	47	24	white	.4166667	2.321673
172.	22	73	47	25	white	1.416667	2.320567
173.	22	75	47	27	white	.0833333	2.316008
174.	22	77	47	29	white	2.083333	2.129515
175.	22	78	47	30	white	3.083333	2.056841
176.	22	80	47	32	white	5.083333	2.160106
177.	22	82	47	34	white	7.083333	2.209372
178.	22	85	47	37	white	10	2.252045
179.	22	87	47	39	white	1.5	2.007068
180.	23	75	46	28	white	.1666667	1.910543
181.	23	77	46	30	white	1.666667	1.854699
182.	23	82	46	35	white	1.583333	1.856298
183.	23	83	46	36	white	2.583333	1.873795

```
184. |     23      87          46     40    white    6.666667    1.796486 |
185. |     24      68          46     21    white    .5833333      1.3722 |
     |-------------------------------------------------------------------|
186. |     24      69          46     22    white    .6666667    1.949388 |
187. |     24      70          46     23    white    1.666667    2.000029 |
188. |     24      71          46     24    white        1.75    2.087567 |
189. |     24      72          46     25    white         .75    2.099055 |
190. |     24      73          46     26    white    1.833333    2.038808 |
     |-------------------------------------------------------------------|
191. |     24      75          46     28    white    3.833333    1.880084 |
192. |     24      77          46     30    white    .3333333    1.806148 |
193. |     24      78          46     31    white    1.416667    1.857954 |
194. |     24      80          46     33    white        3.25    1.998605 |
195. |     24      82          46     35    white        5.25    2.162172 |
     |-------------------------------------------------------------------|
196. |     24      83          46     36    white           0    2.119687 |
197. |     24      85          46     38    white           0    2.307946 |
198. |     24      87          46     40    white           2    2.386735 |
199. |     24      88          46     41    white    3.416667    2.406495 |
200. |     25      77          46     30    white    3.416667    2.109713 |
     +-------------------------------------------------------------------+
```

[10]:
```
qui xtreg ln_wage age tenure i.year, fe
estimates store xtreg_3a
qui areg ln_wage age tenure i.year, absorb(idcode)
estimates store areg_3a
qui xtreg ln_wage age tenure ib(69).year, fe
estimates store xtreg_3b
qui areg ln_wage age tenure ib(69).year, absorb(idcode)
estimates store areg_3b
qui reghdfe ln_wage age tenure, absorb(idcode year)
estimates store reghdfe_3c
estimates table *_3a *_3b *_3c, keep(age tenure) b(%7.4f) se(%7.4f) stats(N)
```

```
--------------------------------------------------------------------------
    Variable | xtreg_3a     areg_3a    xtreg_3b     areg_3b    reghdf~3c
-------------+------------------------------------------------------------
         age |    0.0152      0.0152      0.0114      0.0114   (omitted)
             |    0.0008      0.0008      0.0008      0.0008
      tenure |    0.0219      0.0219      0.0219      0.0219      0.0219
             |    0.0009      0.0009      0.0009      0.0009      0.0009
-------------+------------------------------------------------------------
           N |     23206       23206       23206       23206       22654
--------------------------------------------------------------------------
                                                            legend: b/se
```

- **xtreg** and **areg** produce estimates of the coefficient for *age* even though the coefficient is not identified
- and the estimate changes when the base for the year fixed effect is changed!

2.5 More reasons

- **reghdfe** is usually faster than **areg** or **xtreg**
- **reghdfe** can compute ses with multi-way clustering (Note: with large datasets the order in which you introduce the cluster variables affects performance - always use the variable with highest number of distinct values first)

2.6 Regression with more than one fixed effect (F>1)

With **reghdfe** you can absorb multiple fixed effects. Just add them to the **absorb** option

[11]:
```
clear all
use nlswork
```

```
(National Longitudinal Survey of Young Women, 14-24 years old in 1968)
```

[12]:
```
qui reghdfe ln_wage ttl_exp union not_smsa nev_mar i.year, absorb(idcode)
estimates store reghdfe_4a
qui reghdfe ln_wage ttl_exp union not_smsa nev_mar, absorb(idcode year)
estimates store reghdfe_4b
estimates table *_4a *_4b, keep(ttl_exp union not_smsa nev_mar) b(%7.4f) se(%7.
↪4f) stats(N)
```

```
----------------------------------
    Variable | regh~4a   regh~4b
```

```
-------------+--------------------
     ttl_exp |  0.0437    0.0437
             |  0.0016    0.0016
       union |  0.1010    0.1010
             |  0.0069    0.0069
    not_smsa | -0.0943   -0.0943
             |  0.0124    0.0124
     nev_mar | -0.0209   -0.0209
             |  0.0102    0.0102
-------------+--------------------
           N |   18558     18558
----------------------------------
                      legend: b/se
```

And we can add a third fixed effect:

[13]:
```
reghdfe ln_wage ttl_exp union not_smsa nev_mar, absorb(idcode year occ_code)
```

```
(dropped 665 singleton observations)
(MWFE estimator converged in 17 iterations)

HDFE Linear regression                            Number of obs   =     18,486
Absorbing 3 HDFE groups                           F(   4,  14982) =     245.28
                                                  Prob > F        =     0.0000
                                                  R-squared       =     0.7636
                                                  Adj R-squared   =     0.7083
                                                  Within R-sq.    =     0.0615
                                                  Root MSE        =     0.2508

------------------------------------------------------------------------------
     ln_wage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ttl_exp |    .041726   .0015802    26.41   0.000     .0386286    .0448234
       union |   .0922451   .0068775    13.41   0.000     .0787644    .1057258
    not_smsa |  -.0959395   .0122072    -7.86   0.000    -.1198672   -.0720118
     nev_mar |  -.0210052   .0100888    -2.08   0.037    -.0407804     -.00123
       _cons |   1.443052   .0133288   108.27   0.000     1.416926    1.469178
------------------------------------------------------------------------------

Absorbed degrees of freedom:
-----------------------------------------------------+
 Absorbed FE | Categories  - Redundant  = Num. Coefs |
-------------+---------------------------------------|
      idcode |      3477           0        3477     |
        year |        12           1          11     |
    occ_code |        13           1          12    ?|
-----------------------------------------------------+
? = number of redundant parameters may be higher
```

And it is possible to save the estimates of the fes

[14]:
```
reghdfe ln_wage ttl_exp union not_smsa nev_mar, absorb(fe1=idcode fe2=year␣
 ↪fe3=occ_code)
reghdfe ln_wage ttl_exp union not_smsa nev_mar fe1 fe2 fe3
```

```
(dropped 665 singleton observations)
(MWFE estimator converged in 17 iterations)

HDFE Linear regression                            Number of obs   =     18,486
Absorbing 3 HDFE groups                           F(   4,  14982) =     245.28
                                                  Prob > F        =     0.0000
                                                  R-squared       =     0.7636
                                                  Adj R-squared   =     0.7083
                                                  Within R-sq.    =     0.0615
                                                  Root MSE        =     0.2508

------------------------------------------------------------------------------
     ln_wage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ttl_exp |    .041726   .0015802    26.41   0.000     .0386286    .0448234
       union |   .0922451   .0068775    13.41   0.000     .0787644    .1057258
    not_smsa |  -.0959395   .0122072    -7.86   0.000    -.1198672   -.0720118
     nev_mar |  -.0210052   .0100888    -2.08   0.037    -.0407804     -.00123
       _cons |   1.443052   .0133288   108.27   0.000     1.416926    1.469178
------------------------------------------------------------------------------

Absorbed degrees of freedom:
-----------------------------------------------------+
 Absorbed FE | Categories  - Redundant  = Num. Coefs |
-------------+---------------------------------------|
      idcode |      3477           0        3477     |
        year |        12           1          11     |
    occ_code |        13           1          12    ?|
-----------------------------------------------------+
? = number of redundant parameters may be higher

(MWFE estimator converged in 1 iterations)

HDFE Linear regression                            Number of obs   =     18,486
Absorbing 1 HDFE group                            F(   7,  18478) =    8526.45
                                                  Prob > F        =     0.0000
                                                  R-squared       =     0.7636
                                                  Adj R-squared   =     0.7635
                                                  Within R-sq.    =     0.7636
                                                  Root MSE        =     0.2259
```

```
------------------------------------------------------------------------------
     ln_wage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ttl_exp |    .041726    .000517    80.71   0.000     .0407127    .0427393
       union |   .0922451   .0039496    23.36   0.000     .0845034    .0999868
    not_smsa |  -.0959395   .0037683   -25.46   0.000    -.1033258   -.0885533
     nev_mar |  -.0210052   .0043536    -4.82   0.000    -.0295386   -.0124717
         fe1 |          1   .0053665   186.34   0.000     .9894812    1.010519
         fe2 |          1   .0283374    35.29   0.000     .9444561    1.055544
         fe3 |          1   .0268245    37.28   0.000     .9474214    1.052579
       _cons |   1.443052   .0046049   313.37   0.000     1.434026    1.452078
------------------------------------------------------------------------------
```

It is also possible to add interaction terms

[15]:
```
reghdfe ln_wage union not_smsa nev_mar, absorb(idcode i.year##c.ttl_exp)
```

```
(dropped 666 singleton observations)
(MWFE estimator converged in 11 iterations)

HDFE Linear regression                            Number of obs   =     18,558
Absorbing 2 HDFE groups                           F(   3,  15048) =      85.58
                                                  Prob > F        =     0.0000
                                                  R-squared       =     0.7587
                                                  Adj R-squared   =     0.7024
                                                  Within R-sq.    =     0.0168
                                                  Root MSE        =     0.2535

------------------------------------------------------------------------------
     ln_wage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       union |   .0979223   .0068881    14.22   0.000     .0844207    .1114238
    not_smsa |    -.09025   .0123234    -7.32   0.000    -.1144054   -.0660946
     nev_mar |  -.0123103     .01021    -1.21   0.228    -.0323231    .0077025
       _cons |   1.764868   .0047174   374.12   0.000     1.755621    1.774114
------------------------------------------------------------------------------

Absorbed degrees of freedom:
-----------------------------------------------------+
    Absorbed FE | Categories  - Redundant  = Num. Coefs |
----------------+------------------------------------|
         idcode |      3484           0        3484     |
           year |        12           1          11     |
 year#c.ttl_exp |        12           0          12    ?|
-----------------------------------------------------+
? = number of redundant parameters may be higher
```

[16]:
```
reghdfe ln_wage union not_smsa nev_mar, absorb(i.idcode##c.ttl_exp year)
```

```
(dropped 666 singleton observations)
(MWFE estimator converged in 11 iterations)

HDFE Linear regression                            Number of obs   =     18,558
Absorbing 2 HDFE groups                           F(   3,  11583) =      41.30
                                                  Prob > F        =     0.0000
                                                  R-squared       =     0.8601
                                                  Adj R-squared   =     0.7758
                                                  Within R-sq.    =     0.0106
                                                  Root MSE        =     0.2200

------------------------------------------------------------------------------
     ln_wage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       union |    .077019   .0074498    10.34   0.000     .0624162    .0916219
    not_smsa |   -.061414   .0157465    -3.90   0.000    -.0922799   -.0305481
     nev_mar |   .0054911   .0134288     0.41   0.683    -.0208317    .0318139
       _cons |   1.758235   .0057018   308.37   0.000     1.747058    1.769411
------------------------------------------------------------------------------

Absorbed degrees of freedom:
-----------------------------------------------------------+
      Absorbed FE | Categories  - Redundant  = Num. Coefs |
------------------+----------------------------------------|
           idcode |      3484           0        3484     |
 idcode#c.ttl_exp |      3484           7        3477    ?|
             year |        12           1          11     |
-----------------------------------------------------------+
? = number of redundant parameters may be higher
```

There is much more to **reghdfe**. Places to check are:

- Sergio Correia's website
- Sergio Correia's github
- The related packages:
  - ivreghdfe
  - ppmlhdfe
  - sumhdfe