

# Code documentation

César Garro-Marín\*

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## 1 Notation

Our GMM model is based on the moment equations:

$$\mathbb{E}(\psi(w_i, \mu)) = 0$$

where:

- $w_i$  is the vector of data for observation  $i$ .
- $\psi$  is a  $P \times 1$  vector of functions.
- $\mu$  is an  $R \times 1$  vector of parameters.

We estimate the model's parameters  $\mu$  by solving the problem:

$$\hat{\mu} = \arg \min_c \left( \frac{1}{N} \sum_{i=1}^N \psi(w_i, c) \right)' A \left( \frac{1}{N} \sum_{i=1}^N \psi(w_i, c) \right)$$

which we can write as:

$$\hat{\mu} = \arg \min_c \left( \frac{1}{N} \varepsilon(c)' Z \right)' A \left( \frac{1}{N} Z' \varepsilon(c) \right)$$

where  $\varepsilon(c)$  is the  $N \times 1$  vector of errors of the model, and  $Z$  is the  $N \times P$  matrix of instruments. Here  $N = N_1 + N_2 + N_3$  is the total number of observations and  $N_i$  denotes the number of observations that belong to equation  $i$ .

$\varepsilon(c)$  is defined as follows. Define the functions  $J(l)$ ,  $E(l)$ ,  $T(l)$ , and  $I(l)$  which return the job, education level, year, and skill that correspond to observation  $l$ . In addition, for observations belonging to the employment equation, define as  $EET(l)$  as the function that returns the education pair-year cell of the observation. Then the error for observation  $l$  is:

$$\varepsilon_l(\mu) = \begin{cases} \Delta \ln \overline{S_{ijet+1}} - \sum_k \theta_{ke} \overline{S_{kejt}} \pi_{kjt} + \pi_{ijt} & l \leq N_1 \\ 1 - \sum_k \theta_{ke} \overline{S_{kejt}} & N_1 < l \leq N_1 + N_2 \\ \Delta \left[ \ln \frac{q_{ejt+1}}{q_{e'jt+1}} \right] - \beta_j \left[ \sum_k (\theta_{ke} \overline{S_{kjet}} - \theta_{ke'} \overline{S_{kje't}}) \pi_{kjt} \right] - \gamma_{e,e't} & N_1 + N_2 < l \leq N \end{cases}$$

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\*Boston University, email: [cesarlgm@bu.edu](mailto:cesarlgm@bu.edu)

## 2 GMM standard errors

The GMM estimates are distributed as:

$$\sqrt{N}(\hat{\mu} - \mu) \rightarrow N(0, \tilde{V})$$

where  $\tilde{V} = (D'AD)^{-1}D'AVAD(D'AD)^{-1}$ . Here:

- $D$  is the model gradient.
- $V$  is defined as:

$$V = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N \mathbb{E}(\psi(w_i, \mu)\psi(w_i, \mu)')$$

- $A$  is the weighting matrix  $(Z'Z)^{-1}$

We estimate  $\tilde{V}$  as:

$$\hat{\tilde{V}} = (\hat{D}'A\hat{D})^{-1}\hat{D}'A\hat{V}A\hat{D}(\hat{D}'A\hat{D})^{-1}$$

where:

- $\hat{V} = \frac{1}{N} \sum_{i=1}^N \psi(w_i, \hat{\mu})\psi(w_i, \hat{\mu})'$ .
- $\hat{D} = \frac{1}{N} \sum_{i=1}^N \frac{\partial \psi(w_i, \hat{\mu})}{\partial c'}$

### 2.1 Computing the gradient:

Let  $\Xi$  be the  $N \times R$  matrix with general term  $\Xi_{lr} = \frac{\partial \varepsilon(w_l, c)}{\partial c_r}$ . Then our estimate of the gradient is  $P \times R$  matrix:

$$\hat{D} = \frac{1}{N} Z' \Xi$$

Thus, we just have to compute  $\Xi_{lr}$ . We need to compute derivatives with respect to four types of parameters:  $\theta_{ke}$ ,  $\pi_{kjt}$ , and  $\beta_j$ :

$$\begin{aligned}\frac{\partial \varepsilon_l(\mu)}{\partial \theta_{ie}} &= \begin{cases} -\overline{S_{kejt}}\pi_{ijt} & l \leq N_1, e = E(l), i \neq 1 \\ -\overline{S_{iejt}} & N_1 < l \leq N_1 + N_2, e = E(l), i \neq 1 \\ -\beta_j \overline{S_{ijet}}\pi_{ijt} & N_1 + N_2 < l \leq N, (e, \cdot, \cdot) = EET(l), i \neq 1 \\ \beta_j \overline{S_{ijet}}\pi_{ijt} & N_1 + N_2 < l \leq N, (\cdot, e, \cdot) = EET(l), i \neq 1 \\ 0 & \text{otherwise} \end{cases} \\ \frac{\partial \varepsilon_l(\mu)}{\partial \theta_1} &= \begin{cases} -\overline{S_{kejt}}\pi_{ijt} & l \leq N_1 \\ -\overline{S_{iejt}} & N_1 < l \leq N_1 + N_2 \\ \beta_j \overline{S_{ijet}}\pi_{ijt} - \beta_j \overline{S_{ije't}}\pi_{ijt} & N_1 + N_2 < l \leq N \\ 0 & \text{otherwise} \end{cases} \\ \frac{\partial \varepsilon_l(\mu)}{\partial \pi_{ijt}} &= \begin{cases} -\theta_{ie} \overline{S_{iejt}} & l \leq N_1, i \neq I(l), j = J(l), t = T(l) \\ -\theta_{ie} \overline{S_{iejt}} + 1 & l \leq N_1, i = I(l), j = J(l), t = T(l) \\ -\beta_j (\theta_{ie} \overline{S_{ijet}} - \theta_{ie'} \overline{S_{ije't}}) & N_1 + N_2 < l \leq N \\ 0 & \text{otherwise} \end{cases} \\ \frac{\partial \varepsilon_l(\mu)}{\partial \beta_j} &= \begin{cases} -[\sum_k (\theta_{ke} \overline{S_{kjet}} - \theta_{ke'} \overline{S_{kje't}}) \pi_{kjt}] & N_1 + N_2 < l \leq N, j = J(l) \\ 0 & \text{otherwise} \end{cases} \\ \frac{\partial \varepsilon_l(\mu)}{\partial \gamma_{ee't}} &= \begin{cases} -1 & N_1 + N_2 < l \leq N, (e, e', t) = EET(l) \\ 0 & \text{otherwise} \end{cases}\end{aligned}$$

We compute  $\Xi$  with the function `get_xi_matrix`, and compute  $\bar{V}$  with `estimate_v`. Finally, the function `get_standard_errors` computes the standard errors.

## 2.2 Standard errors for $\sigma_j$ and $d \ln A_{ijt}$

The above derivation gives standard errors for  $\beta_j = \frac{\sigma_j - 1}{\sigma_j}$ . Using the delta method, it is straightforward to compute standard errors for  $\sigma_j = \frac{1}{1 - \beta_j}$ .

$$\sqrt{N}(\hat{\sigma}_j - \sigma_j) \rightarrow N\left(0, \text{var}(\sigma_j) \left[\frac{\partial \sigma_j}{\partial \beta_j}\right]^2\right)$$

where:

$$\left[\frac{\partial \sigma_j}{\partial \beta_j}\right]^2 = \frac{1}{(1 - \beta_j)^2} = \sigma_j^2$$

By an analogous argument:

$$\pi_{ijt} = \frac{\sigma_j}{\sigma_j - 1} d \ln A_{ijt}$$

therefore:

$$d \ln A_{ijt} = \frac{\sigma_j - 1}{\sigma_j} \pi_{ijt} = \beta_j \pi_{ijt}$$

$$\sqrt{N}(d \ln \hat{A}_{ijt} - d \ln A_{ijt}) \rightarrow N\left(0, G(\gamma)' \tilde{V} G(\gamma)\right)$$

where  $\tilde{V}$  is the variance matrix of  $\psi = (\pi_{ijt}, \beta_j)'$  and  $G(\psi) = (\beta_j, \pi_{ijt})'$

Table 1: Summary statistics of teachers in the study sample

Variable	Age arrival USA	Central FPs	Pronouns present	Preverbal pronouns	Preverbal subjects	s-deletion	Liquid- neutralization
<i>A. Puerto Rico</i>							
Pascal	36	0	42.1	94.9	74.6	70.6	73
Priscila	0	100	61.1	100	88.9	68	83
Observations		150	421	222	96	150	168
$\chi^2$ test p-value		***	***	**	*	p = .72	p = .17
<i>B. El Salvador</i>							
Emilio	20	32	29.7	78.7	44.1	16	0
Eduardo	0	93	23.7	98.2	85.2	9	0
Observations		60	479	129	86	150	52
X2 test p-value		***	p = .15	***	***	p = .31	NA
<i>C. Colombia</i>							
Clemente	30	18.9	25.5	94.7	89	14.4	12
Cesar	3	70.8	30.1	95.3	89	6.4	4
Observations		185	1,487	336	454	153	88
$\chi^2$ test p-value		***	*	p = .78	p = .95	p = .11	24
<i>D. Dominican Republic</i>							
David	36	7.2	31.9	98	84	50.7	42
Donaldo	4	92.4	63.5	100	84	26.3	31.7
Observations		205	363	175	100	205	236
$\chi^2$ test p-value		***	***	p = .11	p = .99	***	p = .12
<b>Total observations</b>		600	2750	862	736	658	544
<b>n sig. results</b>		4	3	2	2	1	0

Note: \* =  $p < .05$ , \*\* =  $p < .01$ , \*\*\* =  $p < .001$