

# Replication of Antràs, Fort, and Tintelnot (2017)

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This replication exercise focuses on models of entry. It applies the algorithm first developed by Jia (2008) in order to simplify the problem dimension, and then estimates the parameters via simulated moments.

The replication codes can be found in my github page: <https://github.com/loforteg> .

## 1 Summary

This paper, published in the *American Economic Review* in 2017, applies the iterative algorithm first developed by Jia (2008) to a multi-firm environment where firms self-select into importing based on their productivity and country-specific variables. This multi-country sourcing model differs from canonical export models: global sourcing decisions naturally interact through the firm's cost function, while firms profits coming from exports are additively separable across destination markets.

### 1.1 Theoretical Framework

The authors consider a framework of  $J$  countries where individuals have the same symmetric CES preferences

$$U_{Mi} = \left( \int_{\omega \in \Omega_i} q_i(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}} \quad \wedge \quad \sigma > 1$$

with  $\Omega_i$  being the set of manufacturing varieties available in country  $i \in J$ . Demand for variety  $\omega$  in  $i$  is  $q_i(\omega) = E_i P_i^{\sigma-1} p_i(\omega)^{-\sigma}$ , where  $p_i(\omega)$  is the price of variety  $\omega$  in  $i$ ,  $P_i$  is the ideal price index in  $i$ , and  $E_i$  is the aggregate spending on manufacturing goods in  $i$ . The only factor of production is labour and is paid  $w_i \forall i \in J$ .

There are  $N_i$  final good producers in each country, producing one single differentiated variety each, and thus competing under monopolistic competition with each other. In every country, there is free entry of firms.

The authors employ a time-line similar to the one adopted in Melitz (2003): firms learn their productivity  $\varphi$  after paying an entry cost of  $f_{ei}$  units of labour in  $i$ .  $\varphi$  is drawn from a country-specific distribution  $g_i(\varphi)$ .

Intermediates are produced by a competitive fringe of suppliers selling at their marginal cost under constant returns to scale using only labour:  $a_j(\nu, \varphi)$  is the unit labour requirement associated with the production of firm  $\varphi$ 's intermediate  $\nu \in [0, 1]$  in country  $j \in J$ . The authors then borrow from Eaton and Kortum (2002)

by assuming  $a_j(\nu, \varphi)$  to be distributed according to a Fréchet distribution<sup>1</sup> with scale parameter  $T_j$  and shape parameter  $\theta$ .

To underline the role of sourcing, the authors assume that final goods are not tradable, while intermediates will be traded internationally. Shipping intermediates from country  $i$  to  $j$  is subject to iceberg trade costs  $\tau_{ij}$ . Following the same intuition as before, a final-good producer based in  $i$  can acquire offshoring capability from  $j$  only after incurring a fixed cost of  $f_{ij}$  units of labour. The set of countries for which the firm has paid the fixed cost of offshoring is called *global sourcing strategy* and is going to be denoted by  $\mathcal{J}_i(\varphi) \subseteq J$ . The firm will then choose the optimal source of its inputs, so that the marginal cost of firm  $\varphi$  based in country  $i$  is

$$c_i(\varphi) = \frac{1}{\varphi} \left( \int_0^1 z_i(\nu, \varphi; \mathcal{J}_i(\varphi))^{1-\rho} d\nu \right)^{\frac{1}{1-\rho}} \quad \wedge \quad z_i(\nu, \varphi; \mathcal{J}_i(\varphi)) = \min_{j \in \mathcal{J}_i(\varphi)} \{ \tau_{ij} a_j(\nu, \varphi) w_j \}.$$

In order to close the model, the authors assume a freely tradable non-manufacturing sector which captures a constant share of spending and uses only labour as input. This sector is big enough to pin down wages, so that they can be treated as exogenous when solving for the equilibrium in each country's manufacturing sector.

The equilibrium is found in three steps. First, taking the sourcing strategy  $\mathcal{J}_i(\varphi)$  as given, the firm optimally chooses from which location to source. The authors obtain a result that closely resembles Eaton and Kortum (2002): if  $j \in \mathcal{J}_i(\varphi)$ , the share of intermediate inputs sourced from  $j$  is

$$\chi_{ij}(\varphi) = \frac{T_j(\tau_{ij}w_j)^{-\theta}}{\Theta_i(\varphi)} \quad \wedge \quad \Theta_i(\varphi) \equiv \sum_{k \in \mathcal{J}_i(\varphi)} T_k(\tau_{ik}w_k)^{-\theta} \quad (1)$$

and  $\chi_{ij}(\varphi) = 0$  otherwise.  $\Theta_i(\varphi)$  is defined as the *sourcing capability* of firm  $\varphi$ , while  $T_j(\tau_{ij}w_j)^{-\theta}$  is the *sourcing potential* of  $j$  from the point of view of firms in  $i$ . This result allows to simplify the marginal cost of firm  $\varphi$  in  $i$  as  $c_i(\varphi) = \frac{1}{\varphi} (\gamma \Theta_i(\varphi))^{-\frac{1}{\theta}}$ , where  $\gamma = [\Gamma(\frac{\theta+1-\rho}{\theta})]^{\frac{\theta}{1-\rho}}$ .

Second, the firm optimally chooses its sourcing strategy to maximize its profits:

$$\max_{I_{ij} \in \{0,1\}_{j=1}^J} \pi_i(\varphi, I_{i1}, \dots, I_{iJ}) = \varphi^{\sigma-1} \left( \gamma \sum_{j=1}^J I_{ij} T_j(\tau_{ij}w_j)^{-\theta} \right)^{\frac{\sigma-1}{\theta}} \frac{1}{\sigma} \left( \frac{\sigma}{\sigma-1} \right)^{1-\sigma} E_i P_i^{\sigma-1} - w_i \sum_{j=1}^J I_{ij} f_{ij} \quad (2)$$

where the indicator variable  $I_{ij} = 1$  if  $j \in \mathcal{J}_i(\varphi)$  and takes value of 0 otherwise.

Jia (2008) results will be handy in this step, as solving this maximization problem would entail computing profits for  $2^J$  possible strategies if tackled naively. I will describe it in detail in the computational section.

Third, assuming that consumers spend a constant fraction  $\eta$  of their income on manufacturing, the authors use the free-entry condition to aggregate firm-level decisions and solve for the general equilibrium of the model.

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<sup>1</sup>Recall that this implies  $\Pr(a_j(\nu, \varphi) \geq a) = \exp(-T_j a^\theta)$ . As in Eaton and Kortum (2002),  $T_j > 0$  governs the state of technology in country  $j$  while  $\theta$  determines the variability of productivity across inputs: a lower  $\theta$  implies higher comparative advantage across countries.

## 1.2 Data

The data used in this paper are from the Economic Census, the Longitudinal Business Database, and the Import Transaction database for years 1997 and 2007. Specifically, the authors will focus on firms with at least one manufacturing establishment, positive sales and employment, and will exclude mineral imports.

## 1.3 Structural Analysis

The structural analysis will encompass three steps. First, the authors estimate each country's sourcing potential, taking the sourcing strategy  $\mathcal{J}^n$  as given. Using Equation 1 and defining  $\xi_j \equiv T_j(\tau_{ij}w_j)^{-\theta}$ , the authors obtain

$$\log \chi_{ij}^n - \log \chi_{ii}^n = \log \xi_j + \log \varepsilon_j^n \quad (3)$$

where  $n$  refers to a firm and  $\varepsilon_j^n$  is a firm-country-specific measurement error. Then,  $\xi_j$  is recovered from the estimated coefficient on sourcing country FE. Note that  $T_i(\tau_{ii}w_i)^{-\theta} = 1 \forall i \in J$ .

Second, the authors estimate the elasticity of demand and input productivity dispersion by projecting the estimated sourcing potential  $\xi_j$  on proxies of technology parameter, trade costs, and wages:

$$\begin{aligned} \log \hat{\xi}_j = & \beta_0 + \beta_r \log \text{R\&D}_j + \beta_k \log \text{capital}_j + \beta_f \log \text{number of firms}_j \\ & - \theta \log w_j - \theta(\log \beta_c + \beta_d \log \text{distance}_{ij} + \beta_l \log \text{language}_{ij} + \beta_C \log \text{corruption}_j) + \iota_j \end{aligned} \quad (4)$$

$\theta$  is then recovered from the estimated coefficient on wages.

Lastly, the authors use the method of simulated moments to estimate the fixed costs of sourcing, which are now allowed to vary by firm-country combinations<sup>2</sup>.

Given a core productivity  $\varphi$  and a guess  $\mathcal{J}$  for  $\mathcal{J}^n$ , the marginal benefit of including country  $j$  in  $\mathcal{J}$  is

$$\begin{cases} \varphi^{\sigma-1} \gamma^{\frac{\sigma-1}{\theta}} B(\Theta_i(\mathcal{J} \cup j)^{\frac{\sigma-1}{\theta}} - \Theta_i(\mathcal{J})^{\frac{\sigma-1}{\theta}}) - f_{ij}^n & \text{if } j \notin \mathcal{J} \\ \varphi^{\sigma-1} \gamma^{\frac{\sigma-1}{\theta}} B(\Theta_i(\mathcal{J})^{\frac{\sigma-1}{\theta}} - \Theta_i(\mathcal{J} \setminus j)^{\frac{\sigma-1}{\theta}}) - f_{ij}^n & \text{if } j \in \mathcal{J} \end{cases} \quad (5)$$

Here is where the work from Jia (2008) is applied. The authors define a mapping  $\mathcal{V}_j^n(\mathcal{J})$  that takes a value of one if the marginal benefit is positive, and zero otherwise. This mapping is an increasing function of  $\mathcal{J}$ . When starting from  $\underline{\mathcal{J}} = \emptyset$ , an iterative application of an operator that adds each country to the set one-by-one leads to a lower bound of the firm's sourcing strategy. When starting from  $\overline{\mathcal{J}} = J$ , an iterative application of an operator that adds each country to the set one-by-one leads to an upper bound of the firm's sourcing strategy. When the upper and lower bounds do not overlap, it is only necessary to check the profits from all possible combinations contained in the upper but not the lower bound set.

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<sup>2</sup>  $f_{ij}^n$  is assumed to be drawn from a lognormal distribution with dispersion parameter  $\beta_{\text{disp}}^f$  and scale parameter  $\log \beta_c^f + \beta_d^f \log \text{distance}_{ij} + \beta_l^f \log \text{language}_{ij} + \beta_C^f \log \text{corruption}_j$ .  $f_{ii}^n$  is not identifiable and set equal to 0.

They then assume that firms are distributed like a Pareto, with a shape parameter  $\kappa = 4.25$ , so that there are six parameters to be estimated:  $\delta = [B, \beta_c^f, \beta_d^f, \beta_l^f, \beta_C^f, \beta_{\text{disp}}^f]$ . The authors will simulate a large number of US firms, but there is no relationship between the number of simulated firms and the actual number of firms. Then, they use the simulated firms to construct three sets of moments. First,  $\hat{m}_1(\delta)$ , which is the share of importers for all manufacturing firms and the share of importers with firm sales below the median. Second,  $\hat{m}_2(\delta)$ , the share of firms that import from each country. Third,  $\hat{m}_3(\delta)$ , the share of firms whose input purchases from the US are less than the median US input purchases in the data.

Defining the difference between the moments in the data and the simulated model by  $\hat{y}(\delta) = m - \hat{m}(\delta)$ , the method of simulated moments selects the model parameters as follows:

$$\hat{\delta} = \arg \min_{\delta} \hat{y}(\delta)^T \mathbf{W} \hat{y}(\delta) \quad (6)$$

where  $\mathbf{W}$  is the identity matrix.

## 1.4 Counterfactuals

The authors use their estimates to assess how firm-level import decisions, the firm size distribution, and aggregate sourcing by country respond to a shock in China. The key contribution of performing this counterfactual analysis with their model is that it takes into account the interdependencies characterizing firm-level decisions.

Their main counterfactual exercise is agnostic about the nature of China’s sourcing potential shock. When multiplying the Chinese sourcing potential estimates for 2007 by a factor of 0.46, 5.3 percent of firms start importing from China. The firms that select into sourcing from China increase their input purchase also from the United States and other foreign countries. Firms for which the shock is not large enough to start sourcing from China will face tougher competition and therefore contract their sourcing, especially those from other foreign countries.

## 2 Replication Exercise

Due to limitations in data availability, I can only reply the third step of the estimation process. The first two steps apply an OLS approach to a firm-level dataset, which is not available to me. I will therefore use the estimates for the first two steps reported in Figure 2 and Table 4 of Antràs et al. (2017) to simulate a large number of US firms. As such, I will only be able to replicate Table 5 from the original paper (except the standard deviation).

### 2.1 Steps

I have divided my code in different modules, each tackling a specific part of the estimation procedure.

Module *DGPsetup* simulates a large number of firms according to the parameters that have been estimated by the authors. In the original papers, the authors simulate 2,160,000 firms. Since my computational power is smaller, I have reduced the amount of simulated firms to 216,000.

Module *JiaAlgorithm* is probably the most relevant for this replication exercise. It contains the functions to be used to solve for the optimal set of sourcing countries according to the algorithm developed by Jia (2008). Specifically, there is a function that creates the lower bound  $\underline{\mathcal{J}}$  for each firm, a function that creates the upper bound  $\overline{\mathcal{J}}$  for each firm, and finally a function that finds the optimal set of sourcing countries  $\mathcal{J}$ . This will be given by either the lower or the upper bound, when they coincide, or it checks the countries in between.

In their original paper, the authors characterize three cases when comparing the lower and upper bound: the two sets coincide, the two sets differ by a small number of entries, and the two sets are different for a sizeable number of entries. I struggled defining the second case in my code.

Module *gmmObjectiveFun* computes the estimated moments as well as their difference with respect to data moments.

The main replication file executes these modules sequentially and minimizes the difference between the simulated moments and the data moments. In the original paper, the authors use Matlab's function *fminsearch* with bound constraints. I have replicated their paper using both unconstrained optimization via the *Optim.jl* package, and constrained optimization via the *BlackBoxOptim.jl* package.

However, I noticed something odd in the original codes: the lower bound for the minimization search is bigger than the optimal parameters reported in the papers.

Moreover, the authors parallelize their optimization algorithm by using 10 cores and one different starting guess for each core. I cannot parallelize my work, so I have checked different starting values sequentially.

## 2.2 Results

I am considering the following vectors of guesses:

$$\begin{aligned}
 \delta_0 &= [0.120; 0.020; 0.190; 0.870; -0.390; 0.930] & \delta_1 &= [0.050; 0.100; 0.500; 0.900; 0.100; 1.000] \\
 \delta_2 &= [0.126; 0.182; 0.476; 0.781; 0.451; 0.994] & \delta_3 &= [0.101; 0.081; 0.181; 0.700; 0.703; 1.139] \\
 \delta_4 &= [0.125; 0.030; 0.350; 0.825; 0.275; 1.250] & \delta_5 &= [0.124; 0.028; 0.352; 0.770; 0.361; 1.164] \\
 \delta_6 &= [0.124; 0.023; 0.192; 0.864; 0.392; 0.937] & \delta_7 &= [0.126; 0.011; 0.100; 0.511; 0.200; 1.291] \\
 \delta_8 &= [0.126; 0.011; 0.100; 0.800; 0.150; 0.600] & \delta_9 &= [0.121; 0.159; 0.401; 0.858; 0.792; 0.998] \\
 \delta_{10} &= [0.135; 0.069; 0.537; 0.500; 0.666; 1.460]
 \end{aligned}$$

	B	$\beta_c^f$	$\beta_d^f$	$\beta_l^f$	$\beta_C^f$	$\beta_{\text{disp}}^f$
Antràs, Fort, and Tintelnot (2017)	0.122	0.022	0.193	0.872	-0.393	0.934
	(0.004)	(0.002)	(0.018)	(0.024)	(0.012)	(0.018)
<i>Unbounded optimization</i>						
Optim.jl + $\delta_0$	0.123	0.379	3.530	3.486	0.889	1.036
Optim.jl + $\delta_1$	0.124	0.319	2.752	0.967	-0.237	-0.074
Optim.jl + $\delta_2$	0.124	0.586	1.643	1.031	-0.212	-0.197
Optim.jl + $\delta_3$	0.123	0.770	0.244	4.532	0.038	-0.314
Optim.jl + $\delta_4$	0.123	0.256	1.963	1.103	-0.018	0.189
Optim.jl + $\delta_5$	0.124	0.444	2.932	0.294	-4.698	-0.507
Optim.jl + $\delta_6$	0.124	0.315	1.573	2.672	-2.539	-0.006
Optim.jl + $\delta_7$	0.122	1.358	1.173	0.295	-1.620	-0.023
Optim.jl + $\delta_8$	0.124	0.633	1.709	0.636	-2.427	-0.062
Optim.jl + $\delta_9$	0.123	0.383	0.866	1.615	-0.188	-0.278
Optim.jl + $\delta_{10}$	0.124	0.174	2.313	0.828	-0.734	0.054

Note: I have used a tolerance of  $10^{-5}$ .

My replication estimates for  $B$  seem pretty consistent with the original ones found by the authors. My estimates for the  $\beta$ 's parameters seem to be particularly off. These are the parameters governing the distribution of  $f_{ij}^n$ , the fixed cost of sourcing varying by firm-country combinations.

## 2.3 Issues

The results are clearly very different from those found in the original paper. It may be due to three things:

- a smaller number of simulated firms;
- my version of the Jia algorithm does not have the intermediate case;
- the solver for the optimization step (maybe I am using the wrong method among the solver options).

Since  $B$  is the parameter coming from the Jia (2008) optimization algorithm, and the  $\beta$ 's are the parameters coming from the simulation of firms, I think it is more likely that the difference in the estimates comes from the fact that I have simulated one-tenth of the firms compared to the original paper.

## References

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