

The Economics of Space 433: Section 5

Normalization and Log-Linearization

Costas Arkolakis and Eduardo Fraga¹

¹Yale University

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Goals

- ▶ Our goal in these slides is twofold:
 - ▶ First, we will discuss why our workhorse spatial model features one price normalization
 - ▶ Second, we will work on the algebra of log-linearization.
- ▶ Price normalization:
 - ▶ Equilibrium system has one less equation than it looks (courtesy of Walras's Law)
 - ▶ We then impose one price normalization to “close” the system.
- ▶ Log-linearization:
 - ▶ Express shocks to the equilibrium system and the response of endogenous variables...
 - ▶ ... but in a compact way.

Roadmap

- ▶ **Normalization**
- ▶ Log-Linearization

The Equilibrium System

- ▶ Consider our workhorse spatial model with N locations
- ▶ Given exogenous variables $\{\tau_{ij}, \bar{A}_i, \bar{u}_i\}$ and parameters (α, β, σ) , the equilibrium endogenous variables $\{L_i, w_i, P_i, \bar{W}\}$ are found by solving the following system of equations:

$$w_i L_i = \sum_j \left(\frac{\tau_{ij} w_j}{\bar{A}_i L_i^\alpha P_j} \right)^{1-\sigma} w_j L_j \quad (1)$$

$$\bar{W} = \frac{w_i}{P_i} \bar{u}_i L_i^{-\beta} \quad (2)$$

$$\sum_i L_i = \bar{L} \quad (3)$$

$$P_i = \left(\sum_k \left(\frac{\tau_{ki} w_k}{\bar{A}_k L_k^\alpha} \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \quad (4)$$

Equations and Unknowns

- ▶ Counting the number of equations in the system:
 - ▶ Equation (1) features N equations (one for each location $i = 1, 2, \dots, N$)
 - ▶ Same for equations (2) and (4)
 - ▶ Equation (3) features only one equation.
 - ▶ Total: $3N + 1$
- ▶ Counting the number of unknowns (i.e. endogenous variables) in the system:
 - ▶ Variable w_i features N unknowns, one for each location: w_1, w_2, \dots, w_N
 - ▶ Same for variables P and L
 - ▶ Variable \bar{W} features only one unknown (since welfare is the same everywhere)
 - ▶ Total: $3N + 1$
- ▶ Thus we have an equal number of equations and unknowns:
 - ▶ Suggests that the system has a unique solution for the set of endogenous variables $\{w_i, L_i, P_i, \bar{W}\}$

Walras's Law

- ▶ But wait! We actually have one fewer equation than it appears.
 - ▶ The feasibility equation (1) actually features $N - 1$ equations, not N !
- ▶ Why? Walras's Law



Walrasian Equilibrium

$(\mathbf{p}^*, \mathbf{x}^*)$ such that $\sum_i \mathbf{x}_i(\mathbf{p}^*, \mathbf{p}^* \omega_i) \leq \sum_i \omega_i$

created by:
Martin Messing

- ▶ A principle formulated by Leon Walras in 1874
- ▶ Important Corollary of the Law:
 - ▶ In an economy, if all markets but one are in equilibrium, then that last market must also be in equilibrium
 - ▶ For proof of Corollary, check Appendix slides

Walras's Law in the Spatial Model

- ▶ Apply Corollary to our spatial model's feasibility condition (equation (1)):
 - ▶ If $N - 1$ markets are in equilibrium, then the N th market must also be in equilibrium
 - ▶ Thus, if equation (1) holds for $i = 1, 2, \dots, N - 1$, then it must also hold for $i = N$
 - ▶ N th equation doesn't add any new information!
- ▶ We thought we had N feasibility equations, but we actually have only $N - 1$
 - ▶ The N th equation is redundant!
- ▶ Thus, our equilibrium system only really has $3N$ equations, not $3N + 1$
 - ▶ Which means we have fewer equations ($3N$) than unknowns ($3N + 1$)
 - ▶ System of equations has a potentially infinite number of solutions!

Closing the Model: Price Normalization

- ▶ Therefore, we need one extra equation to “pin down” a single solution from the potentially infinite set of solutions.
- ▶ That’s where price normalization comes in
- ▶ Pick a monetary variable and impose an arbitrarily chosen value to it:
 - ▶ For example, impose $w_1 = 1$ (a practical choice)
 - ▶ Note that other alternative choices would also be valid, e.g. $w_{32} = 12.93\sqrt{37}$ (less practical choice but still valid)
- ▶ With this extra price-normalization equation, we are back to $3N + 1$ equations
 - ▶ The equation system should now have a single solution.
 - ▶ We may now be able to find that solution, either analytically or using numerical methods.

Roadmap

- ▶ Normalization
- ▶ **Log-Linearization**

Log-Linearization

- ▶ In Lecture 13-14 we derived the following equation:

$$\tilde{X}_i = W^{1-\sigma} \sum_j (\tau_{ij}/\bar{A}_i)^{1-\sigma} \tilde{X}_j \quad (5)$$

- ▶ Applying logs and totally differentiating, we will arrive at the following equation:

$$d \ln \tilde{X}_i - \sum_j y_{ij} d \ln \tilde{X}_j - (1 - \sigma) d \ln W = (1 - \sigma) \sum_j y_{ij} d \ln(\tau_{ij}/\bar{A}_i) \quad (6)$$

- ▶ This process is called log-linearization
 - ▶ Equation system becomes expressed in terms of “changes” (hence the d operators) rather than levels
- ▶ Next, we show how to go from equation (5) to equation (6), step by step.

A Few Algebraic Facts

- ▶ Before we start, let's remember a few algebraic facts about logarithms:

$$\text{(F1)} : \ln(ab) = \ln(a) + \ln(b)$$

$$\text{(F2)} : \frac{d \ln(a)}{da} = \frac{1}{a}$$

$$\text{(F3)} : da = a \times d \ln(a)$$

$$\text{(F4)} : d \ln(a) = \frac{da}{a}$$

$$\text{(F5)} : d(m + n) = dm + dn$$

$$\text{(F6)} : \ln a^b = b \times \ln(a)$$

- ▶ Comments:

- ▶ Note that (F3) and (F4) are consequences of (F2)
- ▶ (F5) is reminiscent of the fact that the derivative is a linear operator:

$$\frac{d(f(x)+g(x))}{dx} = \frac{df(x)}{dx} + \frac{dg(x)}{dx}$$

Log-Linearization (1)

- ▶ Let's start the log-linearization process. First take logs of equation (5) and use facts (F1) and (F6):

$$\ln \tilde{X}_i = (1 - \sigma) \ln W + \ln \left(\sum_j (\tau_{ij} / \bar{A}_i)^{1-\sigma} \tilde{X}_j \right)$$

- ▶ Now take differentials of both sides and use (F5):

$$d \ln \tilde{X}_i = (1 - \sigma) d \ln W + d \ln \left(\sum_j (\tau_{ij} / \bar{A}_i)^{1-\sigma} \tilde{X}_j \right)$$

- ▶ Apply (F4) to the latter term:

$$d \ln \tilde{X}_i = (1 - \sigma) d \ln W + \frac{d \left(\sum_j (\tau_{ij} / \bar{A}_i)^{1-\sigma} \tilde{X}_j \right)}{\sum_{j'} (\tau_{ij'} / \bar{A}_i)^{1-\sigma} \tilde{X}_{j'}}$$

- ▶ Apply (F5) to bring the differential operator into the parentheses:

$$d \ln \tilde{X}_i = (1 - \sigma) d \ln W + \frac{\sum_j d \left[(\tau_{ij} / \bar{A}_i)^{1-\sigma} \tilde{X}_j \right]}{\sum_{j'} (\tau_{ij'} / \bar{A}_i)^{1-\sigma} \tilde{X}_{j'}}$$

Log-Linearization (2)

- ▶ Then use (F3) to transform the term inside the square brackets:

$$d \ln \tilde{X}_i = (1 - \sigma) d \ln W + \frac{\sum_j \left[(\tau_{ij} / \bar{A}_i)^{1-\sigma} \tilde{X}_j \right] \times d \ln \left[(\tau_{ij} / \bar{A}_i)^{1-\sigma} \tilde{X}_j \right]}{\sum_{j'} (\tau_{ij'} / \bar{A}_i)^{1-\sigma} \tilde{X}_{j'}}$$

- ▶ Now apply (F1), (F6), and (F5) in succession to term $d \ln \left[(\tau_{ij} / \bar{A}_i)^{1-\sigma} \tilde{X}_j \right]$ to obtain:

$$d \ln \tilde{X}_i = (1 - \sigma) d \ln W + \frac{\sum_j \left[(\tau_{ij} / \bar{A}_i)^{1-\sigma} \tilde{X}_j \right] \times \left[(1 - \sigma) d \ln (\tau_{ij} / \bar{A}_i) + d \ln \tilde{X}_j \right]}{\sum_{j'} (\tau_{ij'} / \bar{A}_i)^{1-\sigma} \tilde{X}_{j'}}$$

Log-Linearization (3)

- ▶ Note that the denominator of the “big fraction”, namely $\sum_{j'} (\tau_{ij'} / \bar{A}_i)^{1-\sigma} \tilde{X}_{j'}$, doesn't depend on j .
 - ▶ Let us then bring it inside the “ \sum_j ” term:

$$d \ln \tilde{X}_i = (1-\sigma) d \ln W + \sum_j \left(\frac{(\tau_{ij} / \bar{A}_i)^{1-\sigma} \tilde{X}_j}{\sum_{j'} (\tau_{ij'} / \bar{A}_i)^{1-\sigma} \tilde{X}_{j'}} \right) \times \left[(1-\sigma) d \ln (\tau_{ij} / \bar{A}_i) + d \ln \tilde{X}_j \right]$$

- ▶ Let's now define term $y_{ij} \equiv \frac{(\tau_{ij} / \bar{A}_i)^{1-\sigma} \tilde{X}_j}{\sum_{j'} (\tau_{ij'} / \bar{A}_i)^{1-\sigma} \tilde{X}_{j'}}$. This greatly simplifies notation:

$$d \ln \tilde{X}_i = (1 - \sigma) d \ln W + \sum_j y_{ij} [(1 - \sigma) d \ln (\tau_{ij} / \bar{A}_i) + d \ln \tilde{X}_j]$$

Log-Linearization (4)

- ▶ Distributing y_{ij} across the terms inside the square brackets and breaking up the summation, we get:

$$d \ln \tilde{X}_i = (1 - \sigma) d \ln W + \sum_j y_{ij} (1 - \sigma) d \ln(\tau_{ij} / \bar{A}_i) + \sum_j y_{ij} d \ln \tilde{X}_j$$

- ▶ Now we just have to rearrange terms across the two sides of the equation to get:

$$d \ln \tilde{X}_i - \sum_j y_{ij} d \ln \tilde{X}_j - (1 - \sigma) d \ln W = (1 - \sigma) \sum_j y_{ij} d \ln(\tau_{ij} / \bar{A}_i)$$

- ▶ This is the same as equation (6)
 - ▶ We've achieved our log-linearization goal!

Roadmap

- ▶ Normalization
- ▶ Log-Linearization
- ▶ **Appendix**

Appendix

- ▶ In this Appendix, we prove the Corollary of Walras's Law
- ▶ Namely, we prove that if all markets but one are in equilibrium, then that last market must also be in equilibrium
- ▶ Formal statement:
 - ▶ If equation (1) holds for $i = 1, 2, \dots, N - 1$, then it must also hold for $i = N$

Proving the Corollary (1)

- ▶ For conciseness of notation, define the variable $\lambda_{ij} \equiv \left(\frac{\tau_{ij} w_i}{\bar{A}_i L_i^\alpha P_j} \right)^{1-\sigma}$
- ▶ For a given destination j , summing across all sources $i = 1, 2, \dots, N$ yields:

$$\sum_{i=1}^N \lambda_{ij} = \sum_{i=1}^N \left(\frac{\tau_{ij} w_i}{\bar{A}_i L_i^\alpha P_j} \right)^{1-\sigma} = P_j^{\sigma-1} \sum_{i=1}^N \left(\frac{\tau_{ij} w_i}{\bar{A}_i L_i^\alpha} \right)^{1-\sigma} = P_j^{\sigma-1} P_j^{1-\sigma} = 1$$

where the penultimate equality comes from the formula of the price index:

$$P_j^{1-\sigma} = \sum_j \left(\frac{\tau_{ij} w_i}{\bar{A}_i L_i^\alpha} \right)^{1-\sigma}$$

- ▶ Multiply both sides of the equation by $w_j L_j$:

$$w_j L_j \sum_{i=1}^N \lambda_{ij} = w_j L_j \Rightarrow \sum_{i=1}^N \lambda_{ij} w_j L_j = w_j L_j$$

Proving the Corollary (2)

- ▶ Now, for both sides of the equation, take the summation across all j 's:

$$\sum_{j=1}^N \sum_{i=1}^N \lambda_{ij} w_j L_j = \sum_{j=1}^N w_j L_j$$

- ▶ On the left-hand side, invert the order of the summations:

$$\sum_{i=1}^N \sum_{j=1}^N \lambda_{ij} w_j L_j = \sum_{j=1}^N w_j L_j \quad (7)$$

- ▶ By hypothesis, we know the following equation holds for $i = 1, 2, \dots, N - 1$:

$$w_i L_i = \sum_j \lambda_{ij} w_j L_j$$

- ▶ So it seems the term $\sum_{j=1}^N \lambda_{ij} w_j L_j$ in equation (7) can be substituted by $w_i L_i$
 - ▶ But be careful! That only works for i from 1 to $N - 1$

Proving the Corollary (3)

- ▶ So, before we can use the hypothesis, let's break " $\sum_{i=1}^N$ " into two parts
 - ▶ One part is from $i = 1$ to $i = N - 1$. The other part is just the final term $i = N$
 - ▶ Equation (7) then becomes:

$$\left(\sum_{i=1}^{N-1} \sum_{j=1}^N \lambda_{ij} w_j L_j \right) + \sum_{j=1}^N \lambda_{Nj} w_j L_j = \sum_{j=1}^N w_j L_j$$

- ▶ Now we can apply the hypothesis to substitute $w_i L_i$ for $\sum_{j=1}^N \lambda_{ij} w_j L_j$ within the first summation:

$$\left(\sum_{i=1}^{N-1} w_i L_i \right) + \sum_{j=1}^N \lambda_{Nj} w_j L_j = \sum_{j=1}^N w_j L_j$$

- ▶ Rearranging terms:

$$\sum_{j=1}^N \lambda_{Nj} w_j L_j = \sum_{j=1}^N w_j L_j - \sum_{i=1}^{N-1} w_i L_i$$

Proving the Corollary (4)

- ▶ Now let's open up the terms in the right-hand side:

$$\sum_{j=1}^N \lambda_{Nj} w_j L_j = (w_1 L_1 + w_2 L_2 + \dots + w_{N-1} L_{N-1} + w_N L_N) \\ - (w_1 L_1 + w_2 L_2 + \dots + w_{N-1} L_{N-1})$$

- ▶ Cancelling terms on the right-hand side, we finally get:

$$\sum_{j=1}^N \lambda_{Nj} w_j L_j = w_N L_N$$

- ▶ That is precisely the feasibility condition (equation (1)) applied to the N th location
 - ▶ That is, we have proved that the N th market is also in equilibrium!
 - ▶ That concludes our proof