Online Supplement to

The Dynamics of Comparative Advantage

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S.1 Adaption of the GMM generated-variable correction to second-stage OLS estimation

To adapt the results in **Appendix D.2** to the decay regression, we need to specify the appropriate moment condition and to account for the use of export capability estimates, instead of treating absolute advantage or comparative advantage as data.

Consider the decay relationship (10) and suppose true export capability were observed. Then, for any time interval Δ such as ten years,

$$k_{is,t+\Delta} - k_{ist} = \rho k_{ist} + \delta_{it} + \delta_{st} + \epsilon_{is,t+\Delta}. \tag{S.1}$$

The OLS estimator for ρ and the residual variance s^2 is the GMM estimator for the following conditional moment

$$\mathbb{E}_{ist}\mathbf{g}(\boldsymbol{\theta}, k_{is,t+\Delta}, k_{ist}; \boldsymbol{\delta}) \equiv \mathbb{E}_{ist}\begin{pmatrix} (k_{is,t+\Delta} - k_{ist} - \rho k_{ist} - \delta_{it} - \delta_{st})k_{ist} \\ s^2 - (k_{is,t+\Delta} - k_{ist} - \rho k_{ist} - \delta_{it} - \delta_{st})^2 \end{pmatrix} = \mathbf{0}, \tag{S.2}$$

where $\boldsymbol{\theta} = (\rho, s^2)'$ and $\boldsymbol{\delta}$ collects the industry-year and country-year fixed effects. We do not calculate a correction for standard errors on the industry-time and country-time fixed effects.

In the decay regression, we work with estimates of export capability directly and only use time series pairs spaced exactly Δ years apart. Let $\mathcal{S}_{it}$ denote the set of countries exporting good i in year t and also export good i in year $t+\Delta$. The effective sample size is $N \equiv \sum_{t=1}^{I}\sum_{t=1}^{T-\Delta}|\mathcal{S}_{it}|$. Denote the OLS estimator of $\boldsymbol{\theta}$ with $\hat{\boldsymbol{\theta}}_N$ and the OLS estimator for $\boldsymbol{\delta}$ with $\hat{\boldsymbol{\delta}}_N$.

A mean value expansion of the GMM criterion function (S.2) evaluated at the export capability estimates and estimates of the fixed effects gives

$$\begin{aligned}\mathbf{g}(\hat{\boldsymbol{\theta}}_N, k^{\text{OLS}}_{is,t+\Delta}, k^{\text{OLS}}_{ist}; \hat{\boldsymbol{\delta}}_N) = &\underbrace{\mathbf{g}\left(\boldsymbol{\theta}_0, k_{is,t+\Delta}, k_{ist}; \boldsymbol{\delta}_0\right)}_{\equiv \mathbf{G}^0_{ist}} + \underbrace{\frac{\partial}{\partial\boldsymbol{\theta}}\mathbf{g}\left(\boldsymbol{\theta}, \tilde{k}_{is,t+\Delta}, \tilde{k}_{ist}; \tilde{\boldsymbol{\delta}}_N\right)\Big|_{\boldsymbol{\theta}=\tilde{\boldsymbol{\theta}}_N}}_{\equiv \tilde{\mathbf{G}}^1_{ist}}(\hat{\boldsymbol{\theta}}_N - \boldsymbol{\theta}_0) \\ &+ \underbrace{\frac{\partial}{\partial k^F}\mathbf{g}\left(\tilde{\boldsymbol{\theta}}_N, k^F, \tilde{k}_{ist}; \tilde{\boldsymbol{\delta}}_N\right)\Big|_{k^F=\tilde{k}_{is,t+\Delta}}}_{\equiv \tilde{\mathbf{G}}^2_{ist}}(k^{\text{OLS}}_{is,t+\Delta} - k_{is,t+\Delta}) + \underbrace{\frac{\partial}{\partial k}\mathbf{g}\left(\tilde{\boldsymbol{\theta}}_N, \tilde{k}_{ist}, k; \tilde{\boldsymbol{\delta}}_N\right)\Big|_{k=\tilde{k}_{ist}}}_{\equiv \tilde{\mathbf{G}}^3_{ist}}(k^{\text{OLS}}_{ist} - k_{ist}),\end{aligned}$$

where $|\tilde{\boldsymbol{\theta}}_N - \boldsymbol{\theta}_0| \leq |\hat{\boldsymbol{\theta}}_N - \boldsymbol{\theta}_0|$, $|\tilde{\boldsymbol{\delta}}_N - \boldsymbol{\delta}_0| \leq |\hat{\boldsymbol{\delta}}_N - \boldsymbol{\delta}_0|$, and $|\tilde{k}_{ist} - k_{ist}| \leq |k^{\text{OLS}}_{ist} - k_{ist}|$. From this mean-value expansion, we obtain

$$\begin{aligned}&\sqrt{N}(\hat{\boldsymbol{\theta}}_N - \boldsymbol{\theta}_0) = \\ &-\left[\tilde{\boldsymbol{\Lambda}}'_N\mathbf{W}\tilde{\boldsymbol{\Lambda}}_N\right]^{-1}\tilde{\boldsymbol{\Lambda}}'_N\mathbf{W}\frac{1}{\sqrt{N}}\sum_{i=1}^{I}\sum_{t=1}^{T-\Delta}\sum_{s\in\mathcal{S}_{it}}\frac{N}{I|\mathcal{S}_{it}|(T-\Delta)}\left[\mathbf{G}^0_{ist} + \tilde{\mathbf{G}}^2_{ist}(k^{\text{OLS}}_{is,t+\Delta} - k_{is,t+\Delta}) + \tilde{\mathbf{G}}^3_{ist}(k^{\text{OLS}}_{ist} - k_{ist})\right]\end{aligned}$$

where $\tilde{\mathbf{\Lambda}}_N = [1/I(T-\Delta)] \sum_{i=1}^{I} \sum_{t=1}^{T-\Delta} (1/|\mathcal{S}_{it}|) \sum_{s \in \mathcal{S}_{it}} \tilde{\mathbf{G}}^1_{ist}$.

The sum in this expression can be rewritten as

$$\frac{1}{\sqrt{N}} \sum_{i=1}^{I} \sum_{t=1}^{T-\Delta} \sum_{s \in \mathcal{S}_{it}} \frac{N}{I|\mathcal{S}_{it}|(T-\Delta)} \left[\mathbf{G}^0_{ist} + \tilde{\mathbf{G}}^2_{ist}(k^{\text{OLS}}_{is,t+\Delta} - k_{is,t+\Delta}) + \tilde{\mathbf{G}}^3_{ist}(k^{\text{OLS}}_{ist} - k_{ist}) \right]$$

$$= \frac{1}{\sqrt{N}} \sum_{i=1}^{I} \sum_{t=1}^{T-\Delta} \sum_{s \in \mathcal{S}_{it}} \frac{N}{I|\mathcal{S}_{it}|(T-\Delta)} \mathbf{G}^0_{ist} + o_p(1)$$

$$+ \frac{1}{\sqrt{N}} \sum_{t=1}^{T} \sum_{i=1}^{I} \underbrace{\sum_{s=1}^{S} \left[\mathbf{1}\{s \in \mathcal{S}_{i,t-\Delta}\} \frac{N}{I|\mathcal{S}_{i,t-\Delta}|(T-\Delta)} \mathbf{G}^2_{is,t-\Delta} + \mathbf{1}\{s \in \mathcal{S}_{it}\} \frac{N}{I|\mathcal{S}_{it}|(T-\Delta)} \mathbf{G}^3_{ist} \right] (k^{\text{OLS}}_{ist} - k_{ist})}_{\equiv \mathbf{L}_{it}}$$

given that

$$\tilde{\mathbf{G}}^2_{ist} \xrightarrow{p} \mathbf{G}^2_{ist} \equiv \left. \frac{\partial}{\partial k^F} \mathbf{g}\left(\boldsymbol{\theta}_0, k^F, k_{ist}; \boldsymbol{\delta}_0\right) \right|_{k^F = k_{is,t+\Delta}},$$

$$\tilde{\mathbf{G}}^3_{ist} \xrightarrow{p} \mathbf{G}^3_{ist} \equiv \left. \frac{\partial}{\partial k} \mathbf{g}\left(\boldsymbol{\theta}_0, k_{is,t+\Delta}, k; \boldsymbol{\delta}_0\right) \right|_{k = k_{ist}}.$$

Define the matrix $\mathbf{G}_{it}$ so that its s'th column is

$$[\mathbf{G}_{it}]_{\cdot s} \equiv \left[\mathbf{1}\{s \in \mathcal{S}_{i,t-\Delta}\} \frac{N}{I|\mathcal{S}_{i,t-\Delta}|(T-\Delta)} \mathbf{G}^2_{is,t-\Delta} + \mathbf{1}\{s \in \mathcal{S}_{it}\} \frac{N}{I|\mathcal{S}_{it}|(T-\Delta)} \mathbf{G}^3_{ist} \right]. \tag{S.3}$$

Then the vector $\mathbf{L}_{it}$ is

$$\mathbf{L}_{it} = \mathbf{G}_{it}(\mathbf{k}^{\text{OLS}}_{i \cdot t} - \mathbf{k}_{i \cdot t}).$$

Based on these derivations, the following proposition states the corrected asymptotic distribution for the coefficients in the decay regression.

Proposition 5. *Under the conditions of Proposition 3 and Assumptions 1, 2, and 3 we have that*

$$\sqrt{N}(\hat{\boldsymbol{\theta}}_N - \boldsymbol{\theta}_0) \xrightarrow{d} \mathcal{N}(\mathbf{0}, (\mathbf{\Lambda}'\mathbf{W}\mathbf{\Lambda})^{-1}\mathbf{\Lambda}'\mathbf{W}(\mathbf{\Xi} + \mathbf{\Omega})\mathbf{W}\mathbf{\Lambda}(\mathbf{\Lambda}'\mathbf{W}\mathbf{\Lambda})^{-1})$$

with

$$\mathbf{\Lambda} \equiv \mathbb{E} \frac{\partial}{\partial \boldsymbol{\theta}} \mathbf{g}\left(\boldsymbol{\theta}_0, k_{is,t+\Delta}, k_{ist}; \boldsymbol{\delta}_0\right),$$

$$\mathbf{\Xi} \equiv \mathbb{E}\mathbf{g}\left(\boldsymbol{\theta}_0, k_{is,t+\Delta}, k_{ist}; \boldsymbol{\delta}_0\right) \mathbf{g}\left(\boldsymbol{\theta}_0, k_{is,t+\Delta}, k_{ist}; \boldsymbol{\delta}_0\right)',$$

$$\mathbf{\Omega} \equiv \lim_{N \to \infty} \frac{1}{ND} \sum_{i=1}^{I} \sum_{t=1}^{T} \mathbf{G}_{it} \mathbf{\Sigma}^*_{it} \mathbf{G}'_{it} / \omega_{it},$$

where the s'th column of the matrix $\mathbf{G}_{it}$ is defined as in (S.3)*, and ω_{it} and $\mathbf{\Sigma}^*_{it}$ are defined as in Appendix D.2.*

Proof. The proof follows the same logic as the proof of Proposition 4, but uses the asymptotic expansion derived in this section. □

S.2 The variance-covariance matrix of η and σ^2

Consider mean reversion of export capability under (S.1):

$$k_{is,t+\Delta} - k_{ist} = \rho k_{ist} + \delta_{it} + \delta_{st} + \epsilon_{is,t+\Delta}.$$

The coefficient ρ measures the fraction of log comparative advantage that dissipates over the time interval Δ. A constant ρ implies that dissipation is symmetric in the sense that export capability below zero reverts towards zero at the same rate as export capability above zero.

Suppose an Ornstein-Uhlenbeck (OU) process generates log comparative advantage $\ln \hat{A}_{is}(t)$ in continuous time, consistent with mean reversion of export capability following (S.1):

$$\mathrm{d} \ln \hat{A}_{is}(t) = -\frac{\eta\sigma^2}{2} \ln \hat{A}_{is}(t)\, \mathrm{d}t + \sigma\, \mathrm{d}W_{is}^{\hat{A}}(t), \tag{S.4}$$

where $W_{is}^{\hat{A}}(t)$ is a Wiener process that induces stochastic innovations in comparative advantage.[45] Equation (S.4) simply restates (11) from the text.

The discrete-time process that results from sampling from an OU process at a fixed time interval Δ is a Gaussian first-order autoregressive process with autoregressive parameter $\exp\{-\eta\sigma^2\Delta/2\}$ and innovation variance $(1 - \exp\{-\eta\sigma^2\Delta\})/\eta$ (Aït-Sahalia et al. 2010, Example 13). Applying this insight to the first-difference equation (S.1), we obtain

$$\begin{aligned} \rho &\equiv -(1 - \exp\{-\eta\sigma^2\Delta/2\}) < 0, \\ s^2 &= (1 - \exp\{-\eta\sigma^2\Delta\})/\eta > 0, \end{aligned} \tag{S.5}$$

as also shown in the main text, where s^2 is the variance of the residual $\epsilon_{is}(t, t+\Delta)$ in (S.1) and the residual is normally distributed with mean zero. The decay model (S.1) is equivalent to an OU process with $\eta > 0$ given the unobserved country fixed effect $\delta_s(t) \equiv \ln Z_s(t+\Delta) - (1+\rho) \ln Z_s(t)$. An OU process with $\rho \in (-1, 0)$ generates a log normal stationary distribution of absolute advantage $A_{is}(t) = Z_s(t)\hat{A}_{is}(t)$ in the cross section, with a shape parameter of $1/\eta$ and a mean of zero.

The two equations (S.5) in (ρ, s^2) can be solved out for the equivalent OU parameters (η, σ^2):

$$\begin{aligned} \eta &= \frac{1 - (1+\rho)^2}{s^2} > 0, \\ \sigma^2 &= \frac{\ln(1+\rho)^{-2}}{\Delta\, \eta} = \frac{s^2}{1 - (1+\rho)^2} \frac{\ln(1+\rho)^{-2}}{\Delta} > 0. \end{aligned} \tag{S.6}$$

To express derivations more compactly, we consider the OU parameter vector $(\eta, \sigma^2)'$ a function $\mathbf{h}(\rho, s^2; \Delta)$ with

$$\begin{pmatrix} \eta \\ \sigma^2 \end{pmatrix} = \mathbf{h}(\rho, s^2; \Delta) \equiv \begin{pmatrix} \frac{1-(1+\rho)^2}{s^2} \\ \frac{s^2}{1-(1+\rho)^2} \frac{\ln(1+\rho)^{-2}}{\Delta} \end{pmatrix}. \tag{S.7}$$

[45] Recall from definition (14) that comparative advantage in continuous time is $\hat{A}_{is}(t) \equiv A_{is}(t)/Z_s(t)$, where $A_{is}(t) = \exp\{k_{is}(t)\}/\exp\{(1/S)\sum_{\varsigma} k_{i\varsigma}(t)\}$ is measured absolute advantage by (7) and $Z_s(t)$ is an unobserved country-wide stochastic trend.

Estimation. The OU process implies that equation (S.1) satisfies the assumptions of the classic regression model. Estimation of (S.1) with ordinary least squares therefore provides us with consistent estimators:

$$(\hat{\rho}, \hat{\boldsymbol{\delta}}')' \equiv (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y} \;\sim\; \mathcal{N}\left((\hat{\rho}, \hat{\boldsymbol{\delta}}')', s^2(\mathbf{X}'\mathbf{X})^{-1}\right) \tag{S.8}$$

$$\hat{s}^2 \equiv \frac{RSS}{N-P} \;\sim\; \frac{s^2}{N-P}\,\chi^2_{N-P},$$

where $\mathbf{y} \equiv \mathbf{J}^S_{i,t+\Delta}\mathbf{k}_{i\cdot,t+\Delta} - \mathbf{J}^S_{it}\mathbf{k}_{i\cdot t}$ is the dependent variable, $\mathbf{X} \equiv [\mathbf{J}^S_{it}\mathbf{k}_{i\cdot t}, \mathbf{I}_{it}, \mathbf{I}_{st}]$ is the $N \times P$ matrix of regressors ($N \equiv \sum_{t=1}^{I}\sum_{t=1}^{T-\Delta}|\mathcal{S}_{it}|$), RSS is the residual sum of squares (the sum of the squared regression residuals), and χ^2_{N-P} denotes a χ^2-distributed variable with $N-P$ degrees of freedom.[46] The variance of the estimator $\hat{\rho}$ is $\mathbb{V}_{\hat{\rho}} = s^2(X'X)^{-1}$, the variance of the estimator $\hat{s}^2$ is $\mathbb{V}_{\hat{s}^2} = 2s^4/(N-P)$ by the χ^2-distribution, and the estimators $\hat{\rho}$ and $\hat{s}^2$ are independent of each other by the properties of the classic regression model. For convenience, we define the variance-covariance matrix between the two estimators as

$$\boldsymbol{\Sigma}_{\rho,s^2} \equiv \begin{pmatrix} \mathbf{V}_{\hat{\rho}} & 0 \\ 0 & \mathbf{V}_{\hat{s}^2} \end{pmatrix} = \begin{pmatrix} s^2(\mathbf{X}'\mathbf{X})^{-1} & 0 \\ 0 & 2s^4/(N-P) \end{pmatrix}. \tag{S.9}$$

By (S.6) and (S.7), the according estimators of the equivalent OU parameters $(\hat{\eta}, \hat{\sigma}^2)$ can be compactly written as the function

$$\begin{pmatrix} \hat{\eta} \\ \hat{\sigma}^2 \end{pmatrix} = \mathbf{h}\big(\hat{\rho}, \hat{s}^2; \Delta\big).$$

By the multivariate delta method, this estimator is normally distributed with

$$\begin{pmatrix} \hat{\eta} \\ \hat{\sigma}^2 \end{pmatrix} \sim \mathcal{N}\Big(\mathbf{h}\big(\rho, s^2; \Delta\big), \nabla_{\{\rho,s^2\}}\mathbf{h}\big(\rho, s^2; \Delta\big) \cdot \boldsymbol{\Sigma}_{\rho,s^2} \cdot \nabla_{\{\rho,s^2\}}\mathbf{h}\big(\rho, s^2; \Delta\big)'\Big), \tag{S.10}$$

where

$$\nabla_{\{\rho,s^2\}}\mathbf{h}\big(\rho, s^2; \Delta\big) = \begin{pmatrix} \frac{\partial\eta}{\partial\rho} & \frac{\partial\eta}{\partial s^2} \\ \frac{\partial\sigma^2}{\partial\rho} & \frac{\partial\sigma^2}{\partial s^2} \end{pmatrix} = \begin{pmatrix} -\frac{2(1+\rho)}{s^2} & -\frac{1-(1+\rho)^2}{s^4} \\ -\frac{2s^2}{\Delta}\frac{\left[1-(1+\rho)^2\right]-(1+\rho)^2\ln(1+\rho)^{-2}}{(1+\rho)^2[1-(1+\rho)^2]^2} & \frac{\ln(1+\rho)^{-2}}{\Delta[1-(1+\rho)^2]} \end{pmatrix}$$

with $\partial\eta/\partial\rho, \partial\eta/\partial s^2, \partial\sigma^2/\partial\rho < 0$ and $\partial\sigma^2/\partial s^2 > 0$ for $\rho \in (-1, 0)$. For clarity, using (S.9) the variance-covariance matrix of the estimator $(\hat{\eta}, \hat{\sigma}^2)'$ can also be rewritten as

$$\nabla_{\{\rho,s^2\}}\mathbf{h}\big(\rho, \hat{s}^2; \Delta\big) \cdot \boldsymbol{\Sigma}_{\rho,s^2} \cdot \nabla_{\{\rho,s^2\}}\mathbf{h}\big(\rho, s^2; \Delta\big)' = \begin{pmatrix} \left(\frac{\partial\eta}{\partial\rho}\right)^2\mathbf{V}_{\hat{\rho}} + \left(\frac{\partial\eta}{\partial s^2}\right)^2\mathbf{V}_{\hat{s}^2} & \frac{\partial\eta}{\partial\rho}\frac{\partial\sigma^2}{\partial\rho}\mathbf{V}_{\hat{\rho}} + \frac{\partial\eta}{\partial s^2}\frac{\partial\sigma^2}{\partial s^2}\mathbf{V}_{\hat{s}^2} \\ \frac{\partial\eta}{\partial\rho}\frac{\partial\sigma^2}{\partial\rho}\mathbf{V}_{\hat{\rho}} + \frac{\partial\eta}{\partial s^2}\frac{\partial\sigma^2}{\partial s^2}\mathbf{V}_{\hat{s}^2} & \left(\frac{\partial\sigma^2}{\partial\rho}\right)^2\mathbf{V}_{\hat{\rho}} + \left(\frac{\partial\sigma^2}{\partial s^2}\right)^2\mathbf{V}_{\hat{s}^2} \end{pmatrix}.$$

Similarly, for the full vector of all estimators $\mathbf{H}(\rho, s^2; \Delta) \equiv (\hat{\rho}, \hat{s}^2, \hat{\eta}, \hat{\sigma}^2)'$ the variance-covariance matrix

[46] As in Appendix D, $\mathbf{k}_{i\cdot t}$ denotes the vector of export capabilities of industry i at time t across countries and $\mathbf{J}^S_{it}$ is a matrix of indicators reporting the exporter country by observation.

Figure S1: **Absolute Advantage and Export Shares**

Source: WTF (Feenstra et al. 2005, updated through 2008) for 133 time-consistent industries in 90 countries from 1962-2007.
Note: The vertical axis shows a country-industry's gravity-based measure of log absolute advantage $\ln A_{ist}$ given by (7), the horizontal axis plots the same country-industry's share of the industry i's global export value: $X_{ist}/(\sum_{\varsigma} X_{i\varsigma t})$.

$\mathbf{Cov} = \nabla_{\{\rho,s^2\}}\mathbf{H}\big(\rho,\hat{s}^2;\Delta\big)\cdot\mathbf{\Sigma}_{\rho,s^2}\cdot\nabla_{\{\rho,s^2\}}\mathbf{H}\big(\rho,s^2;\Delta\big)'$ can be written as

$$\mathbf{Cov} = \begin{pmatrix} \mathbf{V}_{\hat{\rho}} & 0 & \frac{\partial\eta}{\partial\rho}\mathbf{V}_{\hat{\rho}} & \frac{\partial\sigma^2}{\partial\rho}\mathbf{V}_{\hat{\rho}} \\ 0 & \mathbf{V}_{\hat{s}^2} & \frac{\partial\eta}{\partial s^2}\mathbf{V}_{\hat{s}^2} & \frac{\partial\sigma^2}{\partial s^2}\mathbf{V}_{\hat{s}^2} \\ \frac{\partial\eta}{\partial\rho}\mathbf{V}_{\hat{\rho}} & \frac{\partial\eta}{\partial s^2}\mathbf{V}_{\hat{s}^2} & \left(\frac{\partial\eta}{\partial\rho}\right)^2\mathbf{V}_{\hat{\rho}} + \left(\frac{\partial\eta}{\partial s^2}\right)^2\mathbf{V}_{\hat{s}^2} & \frac{\partial\eta}{\partial\rho}\frac{\partial\sigma^2}{\partial\rho}\mathbf{V}_{\hat{\rho}} + \frac{\partial\eta}{\partial s^2}\frac{\partial\sigma^2}{\partial s^2}\mathbf{V}_{\hat{s}^2} \\ \frac{\partial\sigma^2}{\partial\rho}\mathbf{V}_{\hat{\rho}} & \frac{\partial\sigma^2}{\partial s^2}\mathbf{V}_{\hat{s}^2} & \frac{\partial\eta}{\partial\rho}\frac{\partial\sigma^2}{\partial\rho}\mathbf{V}_{\hat{\rho}} + \frac{\partial\eta}{\partial s^2}\frac{\partial\sigma^2}{\partial s^2}\mathbf{V}_{\hat{s}^2} & \left(\frac{\partial\sigma^2}{\partial\rho}\right)^2\mathbf{V}_{\hat{\rho}} + \left(\frac{\partial\sigma^2}{\partial s^2}\right)^2\mathbf{V}_{\hat{s}^2} \end{pmatrix}.$$

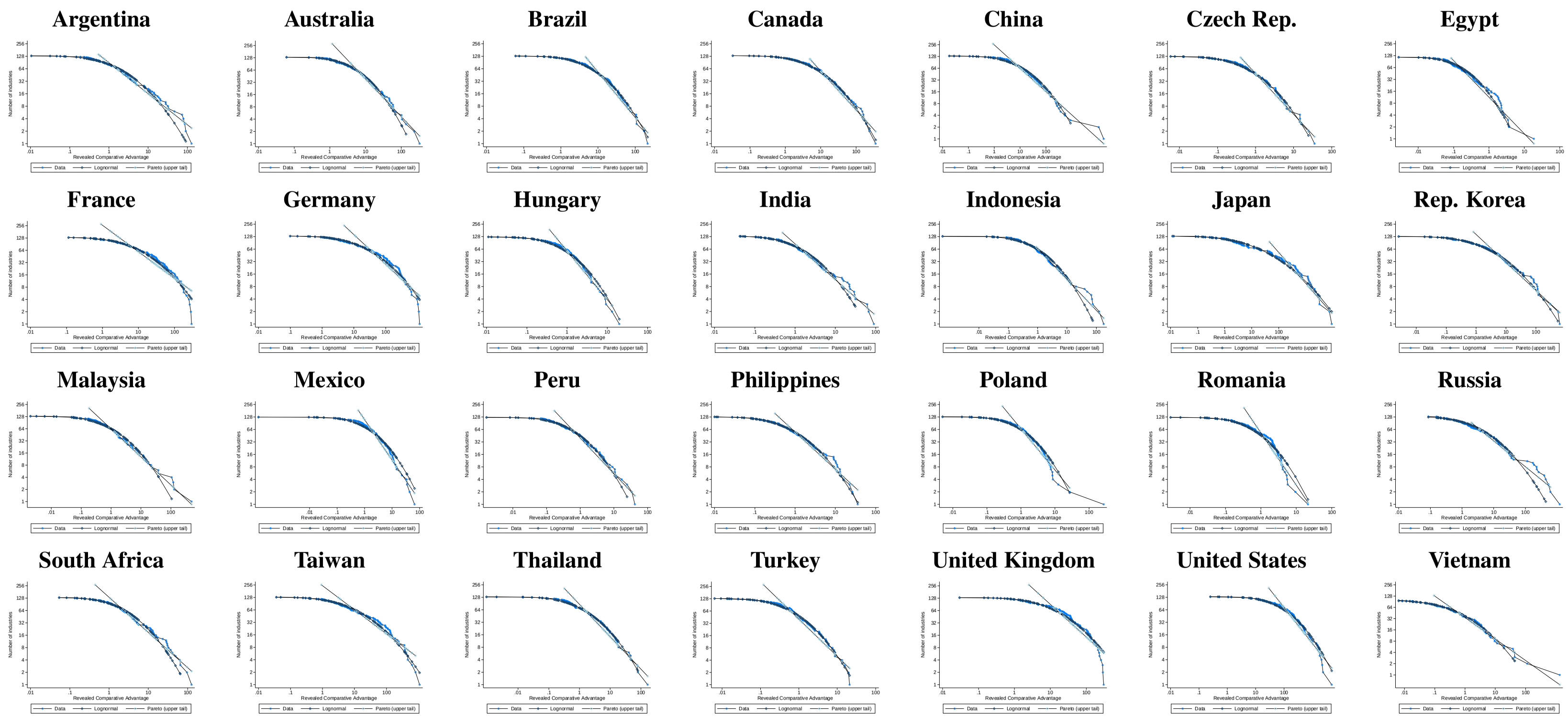
S.3 Absolute advantage and export shares

To verify that our measure of export advantage (7) does not peg obscure industries as top sectors, we plot $\ln A_{ist}$ against the log of the share of the industry in national exports $\ln\Big(X_{ist}/(\sum_j X_{jst})\Big)$. As **Figure S1** documents for the years 1967, 1987 and 2007, there is a strongly positive correlation between log absolute advantage and the log industry share of national exports. This correlation is 0.77 in 1967, 0.78 in 1987, and 0.83 in 2007. (For comparison, the correlation between $\ln A_{ist}$ and the log Balassa RCA index in these same years is 0.69, 0.70, and 0.68, respectively.

S.4 Cumulative probability distribution of Balassa comparative advantage

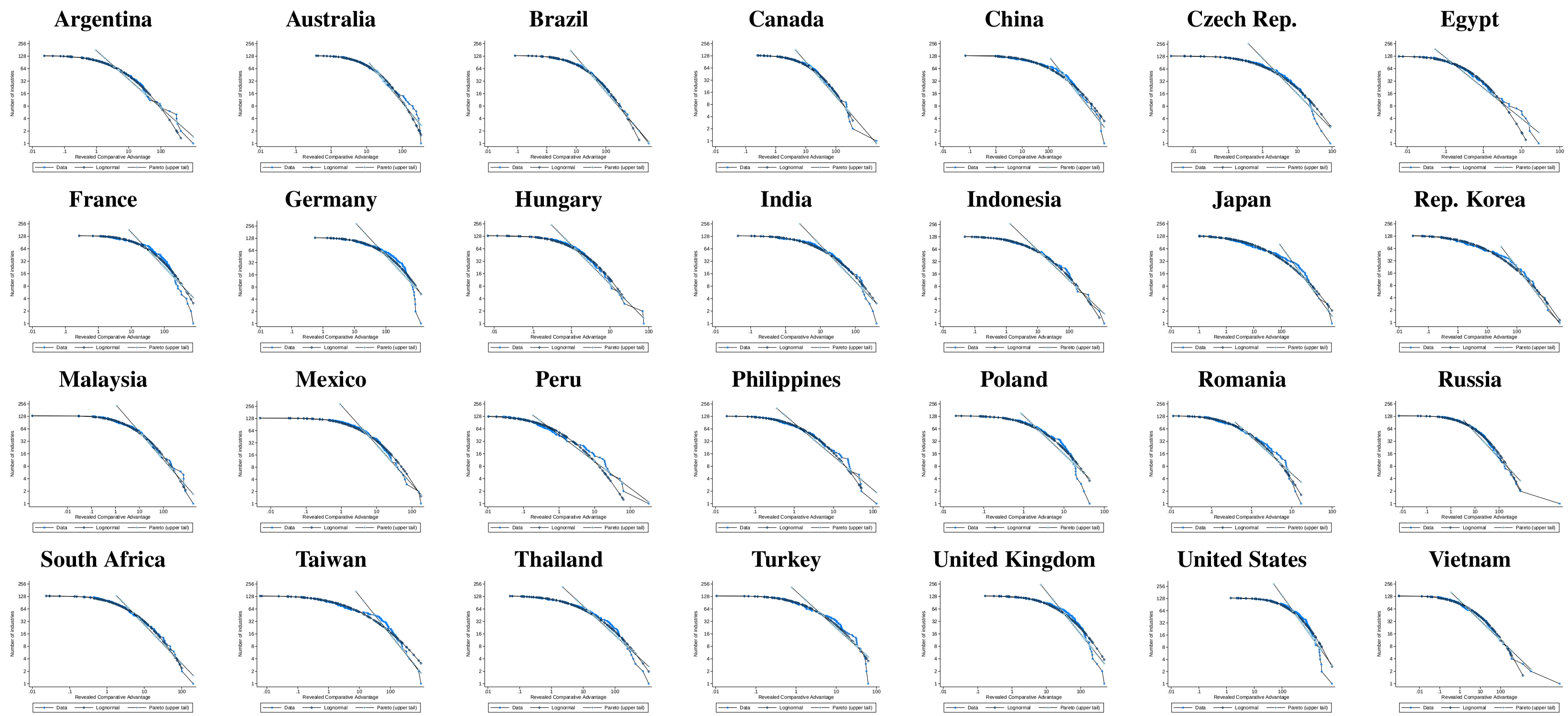
To verify that the graphed cross sectional distributions in **Figures A1, A2** and **A3** in the Appendix to the main paper are not a byproduct of specification error in estimating export capabilities (7) from the gravity model, we repeat the plots using the revealed comparative advantage index by Balassa (1965). **Figures S2** and **S3** plot, for the same 28 countries in 1987 and 2007, the log number of a source country s's industries that have at least a given level of revealed comparative advantage $(X_{is}/\sum_{\varsigma} X_{i\varsigma})/(\sum_j X_{js}/\sum_j\sum_{\varsigma} X_{j\varsigma})$ in year t against that comparative advantage level for industries i. The figures also graph the fit of the revealed comparative advantage index in the cross section to a log normal distribution and to a Pareto distribution using maximum likelihood separately for each country in each year. Results resemble those for export capabilities (7).

Figure S2: **Cumulative Probability Distribution of Balassa Revealed Comparative Advantage for 28 Countries in 1987**



Source: WTF (Feenstra et al. 2005, updated through 2008) for 133 time-consistent industries in 90 countries from 1962-2007.
Note: The graphs show the frequency of industries (the cumulative probability $1 - F_{\hat{X}}(\hat{x})$ times the total number of industries $I = 133$) on the vertical axis plotted against the Balassa index of revealed comparative advantage $\hat{X} = (X_{is}/\sum_{\varsigma} X_{i\varsigma})/(\sum_j X_{js}/\sum_j \sum_{\varsigma} X_{j\varsigma})$ on the horizontal axis. Both axes have a log scale. The fitted log normal distribution is based on maximum likelihood estimation by country s in year $t = 1987$.

Figure S3: **Cumulative Probability Distribution of Balassa Revealed Comparative Advantage for 28 Countries in 2007**

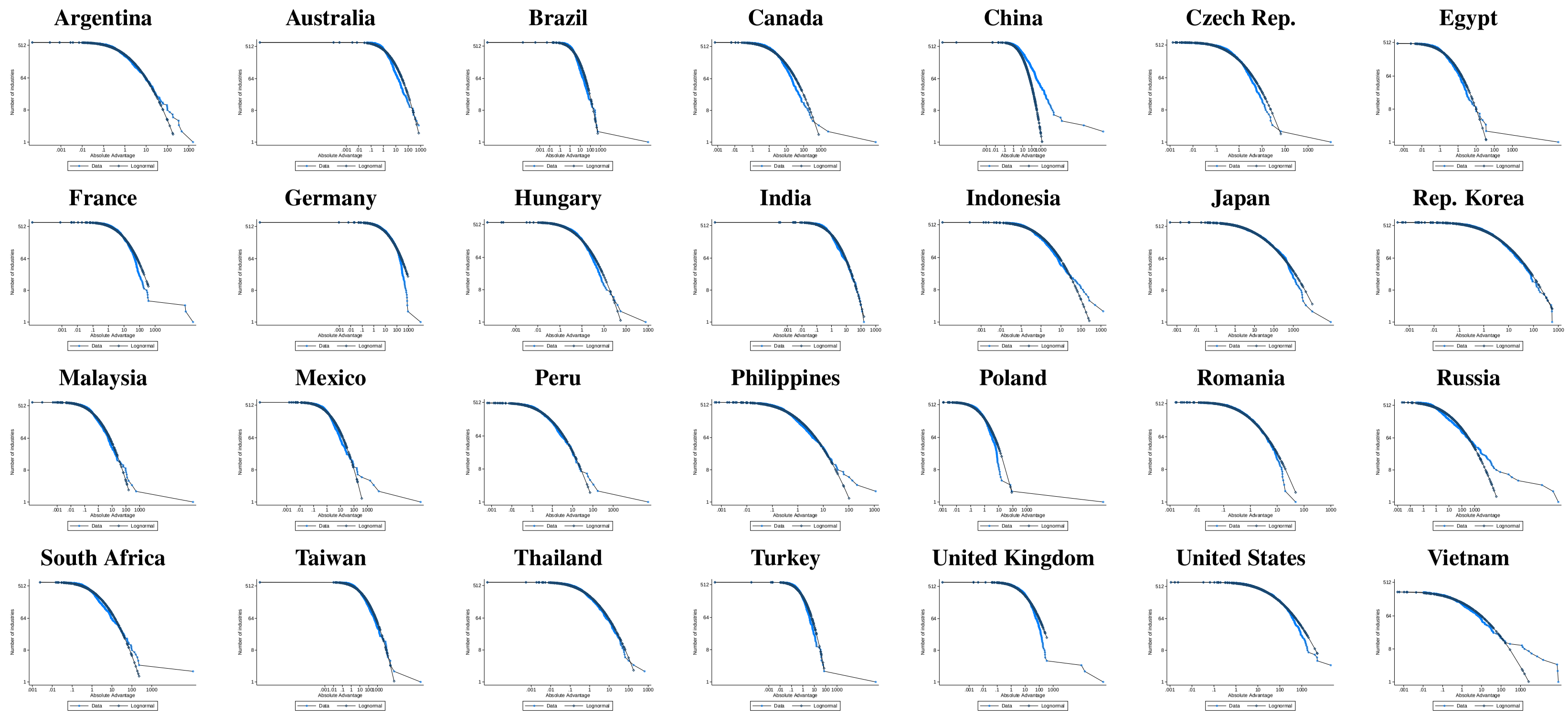


Source: WTF (Feenstra et al. 2005, updated through 2008) for 133 time-consistent industries in 90 countries from 1962-2007.
Note: The graphs show the frequency of industries (the cumulative probability $1 - F_{\hat{X}}(\hat{x})$ times the total number of industries $I = 133$) on the vertical axis plotted against the Balassa index of revealed comparative advantage $\hat{X} = (X_{is}/\sum_{\varsigma} X_{i\varsigma})/(\sum_j X_{js}/\sum_j \sum_{\varsigma} X_{j\varsigma})$ on the horizontal axis. Both axes have a log scale. The fitted log normal distribution is based on maximum likelihood estimation by country s in year $t = 2007$.

S.5 Cumulative probability distribution of log absolute advantage at the SITC 4-digit level

To verify that the graphed cross sectional distributions in **Figures A1, A2** and **A3** in the Appendix are not a consequence of arbitrary industry aggregations, we construct plots also at the 4-digit level based on SITC revision 2 data in 1987 and 2007. The figures also graph the fit of log absolute advantage in the cross section to a log normal distribution using maximum likelihood separately for each country in each year. As **Figures S4** and S5 show for 682 4-digit industries, results resemble those for export capabilities at our benchmark SITC 2-3 digit level for 133 industries.

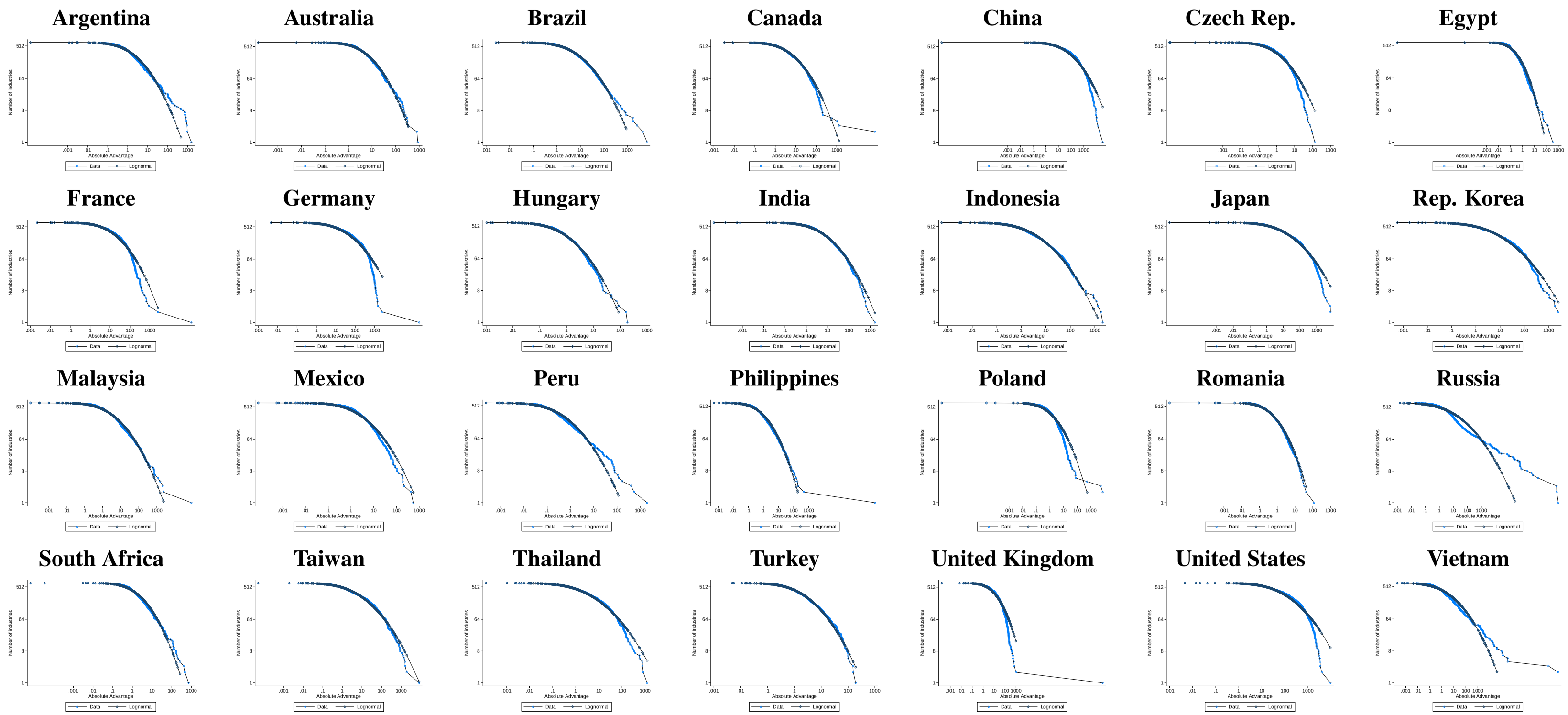
Figure S4: **Cumulative Probability Distribution of Absolute Advantage for 28 Countries in 1987, 4-digit Industries**



Source: WTF (Feenstra et al. 2005, updated through 2008) for 683 time-consistent industries at the 4-digit SITC level in 90 countries from 1962-2007 and CEPII.org; gravity measures of absolute advantage (7).

Note: The graphs show the frequency of industries (the cumulative probability $1 - F_A(a)$ times the total number of industries $I = 683$) on the vertical axis plotted against the level of absolute advantage a (such that $A_{ist} \geq a$) on the horizontal axis. Both axes have a log scale. The fitted log normal distribution are is based on maximum likelihood estimation by country s in year $t = 1987$.

Figure S5: **Cumulative Probability Distribution of Absolute Advantage for 28 Countries in 2007, 4-digit Industries**



Source: WTF (Feenstra et al. 2005, updated through 2008) for 683 time-consistent industries at the 4-digit SITC level in 90 countries from 1962-2007 and CEPII.org; gravity measures of absolute advantage (7).

Note: The graphs show the frequency of industries (the cumulative probability $1 - F_A(a)$ times the total number of industries $I = 683$) on the vertical axis plotted against the level of absolute advantage a (such that $A_{ist} \geq a$) on the horizontal axis. Both axes have a log scale. The fitted log normal distribution are is based on maximum likelihood estimation by country s in year $t = 2007$.